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EDUCATIONAL EVALUATION AND POLICY ANALYSIS 2011 33: 138
DOI: 10.3102/0162373711404220

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Educational Evaluation and Policy Analysis
June 2011, Vol. 33, No. 2, pp.138–158
DOI: 10.3102/0162373711404220
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Public School Response to Special Education Vouchers: The Impact of Florida's McKay Scholarship Program on Disability Diagnosis and Student Achievement in Public Schools

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The authors expand on research evaluating public school response to school choice policies by considering the particular influence of voucher programs for disabled students—a growing type of choice program that may have different implications for public school systems from those of more conventional choice programs. The authors provide a theoretical framework to show that special education vouchers could influence both school quality and the likelihood that a school will choose to identify the marginal child as disabled. Using a rich panel data set from Florida, the authors find some evidence that competition from a voucher program for disabled students decreased the likelihood that a student was diagnosed as having a mild disability and was positively related to academic achievement in the public schools.

Keywords: *special education, vouchers, McKay Scholarship Program, school choice, competitive effects*

THE past two decades have yielded considerable research evaluating public school responses to school choice policies. Gill and Booker's (2008) recent review of the research is typical: They conclude that this research provides reason for "cautious optimism" that school choice programs improve the quality of schooling provided in public schools, though the overall effect appears to be mild.[1]

However, to date there has been no work evaluating public school responses to voucher programs targeted to disabled students. Research specific to special education voucher programs is important because the unique funding arrangement under which special education programs operate could impose different incentives on public school systems than are present under more conventional school choice programs. Understanding the influence of these policies is essential if only because they have recently expanded across the country: Voucher programs for disabled students are operating statewide in Florida, Georgia, Louisiana, Oklahoma, and Utah, such a policy was operating in Arizona until it was struck down by the state's supreme court, and Ohio has adopted a similar program specifically for autistic students.

We discuss two potential public school responses to special education voucher programs. We show that under certain reasonable assumptions special education vouchers will make a school less likely to identify a child as disabled. We utilize existing theory to show that special education voucher programs have implications for the quality of schooling provided to both special education and regular enrollment students. The predictions depend primarily on the school's

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response to the existence of a financial incentive to diagnose students as disabled, evidence for which has been found in prior empirical research.

We empirically test these predictions using a rich panel data set from Florida, which is home to the nation's first and largest voucher program exclusively available to disabled students. We provide some evidence of a negative relationship between the amount of competition that a public school faces from Florida's special education voucher program and the likelihood that a child is identified as having a specific learning disability (SLD)—a mild disability classification for which there is a large subjective component in diagnosis. We also find some evidence that competition from special education vouchers had a positive influence on the math and reading proficiency of public school students.

Special Education Vouchers—Florida's McKay Scholarship Program

Because school choice and voucher programs vary dramatically, it is important that our discussion take place within a specific policy framework. In this article we have in mind a program that operates under the same principles as Florida's McKay Scholarship Program for Students with Disabilities (from here, McKay). We chose McKay as our basis for discussion not only because it is the focus of our empirical analysis but also because it is the nation's first and largest voucher program for disabled students and has served as a template for several other recent programs.

McKay is a statewide program designed to provide parents of disabled students with the resources necessary to attend another public school or a private school if they so choose. McKay provides scholarships to any student who was enrolled in the Florida public school system during the prior year and has been assigned an individualized education program (IEP)—essentially a contract between the school district and the parents that describes the services that the school must provide to the child to meet his or her special needs. Once a student uses a McKay voucher he or she remains eligible for the program until he or she graduates from high school or turns 22 years of age. In 2008–2009 there were 351,179 students with an IEP enrolled in a Florida public school.[2]

Enrollment in the McKay program has grown dramatically. From the time it was first adopted statewide in 2000–2001, the number of students using a scholarship has increased from 970 to 20,096. More than half of the students using a McKay voucher have a disability that is in the least severe matrix, which is similar to the percentage of public school disabled students in this category. About 47% of enrolled students are White, 69% are male, and 42% are eligible for free or reduced-price lunch.[3]

The substantial increase in the number of students using a McKay scholarship is in large part the result of the increase in the number of private schools willing to accept the voucher, which grew from 100 schools in 2000–2001 to 888 schools in 2008–2009. To participate in the program, private schools must meet safety requirements and must employ teachers with at least a bachelor's degree. About 64% of participating schools have a religious affiliation.[4] Unlike many other school voucher programs, private schools are not required to accept the voucher amount as full tuition payment and are not required to accept all applicants.

McKay is also distinguished from other voucher programs by the generosity of the scholarship amount. Eligible students are provided with a voucher equivalent to the lesser of the total amount of dollars that would have been spent on the child in the public school he or she is exiting or the amount of the tuition charged to the student at the accepting private school. According to the Florida Department of Education, in 2006–2007 the amount of a McKay scholarship ranged from $5,039 to $21,907, with an average of $7,206.[5]

The Potential for Strategic Disability Diagnosis

Students generally do not enter public schools with a disability diagnosis. Schools play an active role in classifying students into special education.

The process of identifying a student as disabled begins with a referral from a school employee or a parent. The child is then tested for the presence of a disability by an expert employed by the school district, who decides whether the child is disabled. If the child is diagnosed, then federal law requires that the school develop an IEP.

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In the case of severe disabilities, the student's placement into special education can be thought of as being exogenously given to the school. However, there is often a substantial subjective component to the diagnosis of mild disabilities, which opens the door for strategic diagnosis. When given the opportunity, schools appear responsive to incentives to diagnose students as disabled. For instance, recent work finds that schools appear to place additional low-performing students into special education programs to exempt them from state accountability programs based on high-stakes standardized tests (Cullen & Reback, 2002; Figlio & Getzler, 2002; Jacob, 2005).

Schools might also alter the rate at which they diagnose students in response to the underlying financial incentives to provide a student with special education services. Most states fund special education on a per-child basis, which implies that schools maximize the amount of revenue brought in by a child by identifying him or her as disabled. If additional funding tied to a student's disability classification outweighs the additional cost of providing services required by his or her IEP then the school has a financial incentive to diagnose the child.

Prior empirical research suggests that disability classifications are sensitive to changes in the financial incentive to provide special education services. Using policy-induced variation in state aid generated for disability classifications in Texas, Cullen (2001) estimates that financial incentives accounted for nearly 40% of the growth in special education in Texas during the early 1990s. Kwak (2008) finds a similar result in California. Greene and Forster (2001), Mahitivanichcha and Parrish (2005), and Dhuey and Lipscomb (2008) use state-level panel data and find that the growth in special education enrollments in a state slows when it weakens the financial incentive to diagnose students.

Since schools have little to no influence on whether a severely disabled child is placed into special education, in this article we focus on the influence of vouchers for students who are or might be diagnosed with a mild disability. Our empirical analyses consider how vouchers relate to SLD, which is a particular type of mild disability that is widely thought to suffer from strategic diagnosis.

SLD is defined as "a disorder in one or more of the basic psychological processes involved in understanding or in using language, spoken or written, which may manifest itself in an imperfect ability to listen, think, speak, read, write, spell or do mathematical calculations."[6] The SLD category includes conditions such as perceptual handicaps, developmental aphasia, and dyslexia. Among the criteria used to determine whether a child has an SLD are subjective assessments such as that "the child does not achieve adequately for the child's age or to meet state-approved grade-level standards . . . when provided with learning experiences and instruction appropriate for the child's age or State approved grade-level standards."[7]

Though they receive supplemental services under special education, students with mild disability classifications such as SLD tend to spend most of their school time in general education classrooms. According to the U.S. Department of Education, 59% of SLD students in the United States spent 80% or more of their time in a general classroom environment and only 15% of SLD students spent 60% or more of their time outside of a general class.[8]

One reason to focus on SLD is that there is considerable reason to believe that its diagnosis might be particularly vulnerable to the influence of factors independent of the incidence of true disability. Macmillan and Siperstein (2001) suggest that pubic schools use low achievement alone in the diagnosis of SLD rather than any real clinical diagnosis of a problem learning material. Shepard, Smith, and Vojir (1983) estimated that more than half of the students identified as SLD in Colorado did not fit either federal or state definitions for the disorder. Furthermore Ysseldyke, Algozzine, and Epps (1983) and Ysseldyke, Algozzine, Shinn, and McGue (1982) found that many SLD students are indistinguishable from low-achieving regular enrollment students.

SLD has special policy significance because it is by far the largest special education category. Currently, more than 1 in 20 public school students in the United States have been diagnosed as having an SLD, and the category accounts for 39% of students receiving special education services in the United States.[9]

Theoretical Framework

To fix ideas and motivate estimation, in this section we discuss theoretical predictions for two

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responses to competition for disabled student enrollment induced by vouchers: changes in the likelihood that a school acts to diagnose a child as disabled and the influence on school quality.

Special Education Vouchers and Disability Diagnosis

We first consider a simple model for the school's choice of whether or not to diagnose a child whose special education status it can influence. The model relies on and highlights a unique feature of special education vouchers: Public schools play an active role in determining whether students are eligible to use a voucher.

The model's predictions hinge on the existence of a financial benefit to classifying students as disabled and the influence that vouchers have on the likelihood that a school will receive that premium. If a student uses a voucher, his or her previous public school not only fails to collect the additional funding tied to his or her special education status but also, because it no longer enrolls the student, loses the entirety of the per-pupil funding tied to the child. Profit-maximizing public schools must then consider the probability that a student will utilize a voucher when deciding whether to diagnose him or her as disabled.[10]

Consider the profit-maximizing school's decision to classify a student as disabled in absence of vouchers. The school takes as given the per-pupil resources provided by the state to educate the child in a regular enrollment environment (R^n) and the cost of providing those services (C^n). If the school identifies the child as disabled, it is granted additional revenue to provide special education services to the child (R^s), and it will also be confronted with costs for providing those services (C^s). Formally,

$$Max\Pi = R^n - C^n + \alpha\,(R^s - C^s) \qquad \alpha = 1,0, \qquad (1)$$

where α is the school's choice variable and equals one if the child is in special education and zero otherwise.

The school's decision depends on whether the marginal revenue achieved from diagnosing the child as disabled (R^s) is greater than the marginal cost of providing those services (C^s). If providing special education services is profitable, then the school maximizes its profit by diagnosing him or her. On the other hand, if the marginal cost of providing the student with special education services outweighs the additional revenue brought in to provide those services, then the school will prefer to leave the child in regular education.

According to this overly simplified model, if given the opportunity the school will choose to identify each or none of its students as disabled depending on the marginal revenue and marginal cost of providing those services. However, in practice political and regulatory constraints prevent a school from either of those extreme actions.

We now consider the school's choice in the presence of a special education voucher program. The school's profit function must now include the potential that the student uses a voucher to leave for a competitor. If the child uses a voucher then the public school relinquishes the additional revenue for providing special education services to the child and is not imposed with the costs of providing those services. In addition, the voucher-using student takes with him or her all of the per-pupil resources provided to educate him or her in regular education programs as well as the costs of providing those services. The school's expected profit for educating the child can thus be modeled as,

$$\begin{aligned} MaxE(\Pi) = R^n - C^n + \alpha\{&(1-p)(R^s - C^s) \\ &-p(R^n - C^n)\} \qquad 0 \le p \le 1, \end{aligned} \qquad (2)$$

where p is the probability that the student leaves the public school with a voucher, which we treat as exogenous in this simplified model. The school's decision whether or not to identify the child as disabled in a world with vouchers depends on the likelihood that the child will leave for a competitor.

It is illustrative to consider extreme values for p. First, consider the school's expected profit if there is zero probability that the child will utilize a special education voucher ($p = 0$). This scenario could feasibly occur for rural schools, for example, that have no private school competitors nearby. In this case the school's choice is equivalent to its choice in absence of the voucher program. The school will again choose to identify the child as disabled ($\alpha = 1$) if the marginal revenue brought in from placing him or her into special education outweighs the marginal cost of providing the additional services, and it will choose not

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to classify the student as disabled if the cost of providing special education services outweighs the additional revenue brought in to do so.

Now we consider the other extreme case in which the public school knows for certain that a student will utilize a voucher if given the opportunity ($p = 1$). In this case, the school earns zero profits from the child if it places him or her into special education. The student brings in no revenue and the school bares no cost for educating him or her. Thus, a school that is certain to lose a student to vouchers if he or she becomes eligible to use them will prefer not to identify the child as disabled as long as it is profitable to educate him or her as a regular enrollment student ($R^n - C^n > 0$).

Of course, schools do not often know for certain that a particular child will or will not utilize a special education voucher before they diagnose him or her. Schools will act on the expected value of their profit function given the perceived likelihood that the student will utilize a voucher.

The model's predictions for how introduction of special education vouchers would affect disability diagnoses depend on the relative size of the revenue and cost of providing educational services. We impose two reasonable assumptions to guide our expectations for empirical estimation. First, we assume that the funding that schools receive to educate regular enrollment students is at least as large as the cost of providing those educational services: $R^n - C^n \geq 0$. Were this not the case, then public schools would lose money for every nondisabled student who it educated, which seems implausible. Our second assumption is that schools believe that it is profitable to educate students in special education. That is, we assume that $R^n - C^n > 0$. The earlier discussed findings from previous research that disability diagnoses are responsive to changes in the financial incentive to place students into special education suggests that this assumption is reasonable.

With these two assumptions imposed, the model predicts that competition from vouchers will reduce the profit-maximizing public school's willingness to place a student into special education. That is, in our empirical estimation we expect to find a negative relationship between competition from a special education voucher program and the likelihood that a child is identified as having a mild disability.

Public School Quality in the Presence of Special Education Vouchers

We draw from a wide body of theoretical research considering the influence of conventional voucher programs to develop our expectations for the influence of special education vouchers on the academic achievement of students who remain in public school.[11] Although the mechanisms by which special education vouchers could influence the quality of services provided in public school are the same as those that underlay more conventional choice policies, there are some important distinctions in the case of special education vouchers that are worthy of consideration.

We adopt the school quality function described by Nechyba (2003) to consider the influence of school choice on public school quality to consider the particular influence of special education vouchers. A school combines its per-pupil resources (x) and average peer quality (q) to produce school quality (s). The production process takes the form,

$$s = f(x,q) = \lambda\, x^{1-a} q^{a} \quad \textit{where } 0 < a < 1. \qquad (3)$$

The role of λ is to represent the school's production technology such that if $\lambda = 1$ then the school is utilizing its per-pupil resources to maximum efficiency. In this model, school quality changes only if there is a change in the quality of peers within the school, changes in the amount of school resources, or if the school utilizes its resources in a more efficient manner.

Conventional vouchers are thought to influence each of the school production factors: λ, x, and q. A common theoretical finding in research considering universal voucher programs is that vouchers will tend to decrease peer quality in public schools because private schools can discriminate against low-performing applicants (see, e.g., Epple & Romano, 1998). Vouchers are also thought to improve the school's production technology by breaking its monopoly on enrollment, which forces them to compete in a market for students. Finally, if the voucher is worth less than the per-pupil allocation that the public school would receive to educate the child, then each student who utilizes a voucher will tend to increase the public school system's per-pupil resources.

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The above education production function has proven a powerful tool with which to consider the influence of vouchers on student achievement. Because the model specifies only the production process, its framework should be sufficient for considering the influence of special education vouchers. However, we argue that there are several ways that the unique nature of special education alters how vouchers targeted to disabled students influences the factors of educational production.

The first difference between special education vouchers and more conventional choice programs is that, almost by definition, vouchers that are available only to disabled students do not allow private schools to "cream skim" a public school's highest achieving students. Special education students are usually among the lowest performing students in a school. In fact, most students who have been identified as having a mild disability such as SLD were referred to be tested for special education services precisely because they were struggling academically. Thus, unlike more conventional voucher programs that are utilized by regular enrollment students, use of special education vouchers should tend to improve overall peer quality within a school as its lowest performing students leave for the private sector.

It is possible that private schools would enroll only the highest performing among disabled students. In such a case, voucher-exiting students would increase overall peer quality within a public school while simultaneously decreasing the peer quality among the school's special education population. In the case of mildly disabled students—who are the focus of our analysis—we argue that it is the change in overall school peer quality that is particularly important since, as previously noted, such students tend to spend the large majority of their school time in general classrooms.

Thus, in stark contrast to the universal voucher circumstance, the influence of special education vouchers on peer quality should be such that it is expected to improve school productivity. In addition, these peer effects should work to improve the achievement both of disabled students and also of regular enrollment students who share classrooms with fewer low-performing classmates than they would in absence of vouchers.

The second piece of the school production process relates to the level and efficient use of per-pupil resources. The situation is again different in the case of special education vouchers than for more conventional programs.

If the marginal revenue brought in to serve disabled students outweighs the marginal cost of providing special education services, then we would expect special education vouchers to achieve a competitive effect similar to that of more conventional programs. Either the school might respond by improving special education services or, since mildly disabled students spend most of their time in general education classrooms, the school might make more general improvements that affect the proficiency of regular enrollment students as well. On the other hand, if schools believe that they lose money serving disabled students, then they would be expected to reduce the quality of special education services they provide in hopes of driving such costly students off of their books.

Finally, special education vouchers likely influence school financial resources. It is true that, as in the case of regular enrollment vouchers, the money tied to special education vouchers is limited to be no greater than what the public school would have spent to educate the child. However, if special education students are profitable to educate—that is, in the language of the previous model, if $R^s - C^s > 0$—then as schools lose students to vouchers their total per-pupil resources will also decline, which would tend to decrease total school quality.

Thus, the theoretical expectation for the influence of special education vouchers on student achievement is ambiguous. The influence of special education vouchers on peer quality and in invoking a competitive response should tend to improve public school quality, and those improvements might be felt by both disabled and nondisabled students. However, if special education students are profitable to educate, then losing their enrollment to special education vouchers will decrease school resources available to all students in the school and thus could harm school quality.

Empirical Analysis

We use a rich data set from Florida to test our theoretical predictions. We first evaluate whether there is a relationship between competition from the McKay voucher program and the likelihood that a public school identifies a student as disabled. We then evaluate whether competition from

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TABLE 1
Voucher-Accepting Private Schools by Year

	Statewide totals		Within 5 miles			
	Voucher-using students	Voucher-accepting private schools	Average number of voucher-accepting private schools	*SD*	Min	Max
2001–2002	5,013	296	3.3	3.7	0	18
2002–2003	9,130	518	5.4	5.3	0	27
2003–2004	13,739	687	6.9	6.6	0	31
2004–2005	15,910	708	7.0	6.6	0	31

McKay is related to the academic achievement of students who remain in public schools.

Identification Strategy

The primary difficulty with studying public school reactions to a school choice program is to identify variation in the program's availability. Since all Florida schools became subject to the McKay program at the same time, we cannot simply use the timing of the program's adoption to identify its effects. We follow several other articles and use differences in the number of educational options available over time within a geographic radius to the public school as a measure of differential exposure to the program (see Bettinger, 2005; Bifulco & Ladd, 2006; Booker, Gilpatric, Gronberg, & Jansen, 2008; Buddin & Zimmer, 2004; Sass, 2005).

The motivation behind our procedure is that parents have ready access to schools within a certain radius of their home but less access to schools outside this radius because of the additional travel burden. We assume that schools surrounded by fewer McKay-accepting schools were affected less by the threat of competition from the program because students had access to fewer options. That is, we assume that the probability that a student utilizes a voucher if he or she is diagnosed (p in Equation 2) is greater in schools that are surrounded by more competing private schools willing to accept the voucher.

In each analysis our strategy is to utilize as a measure of McKay exposure the number of voucher-accepting private schools that are within a 5-mile radius of the student's public school in a given year. Table 1 shows that during the years of our analysis, school years 2002 through 2005, there was a substantial increase in the number of schools willing to accept McKay vouchers as at least partial tuition payment.

The vast majority of the increase in McKay competing schools derives from existing private schools making themselves eligible for the policy rather than new schools opening to take advantage of it. Our procedure assumes that a private school imposes competitive pressure on a nearby public school only once it has made itself eligible to receive vouchers. We test that assumption in a later section.

A potentially serious limitation with relying on differential exposure to the McKay program by time and location is that participating private schools are not randomly distributed around public schools. Private schools choose to participate in the program. Estimation will be biased if the number of voucher-accepting private school alternatives within a 5-mile radius of a public school in a given year correlates with other factors for which the model does not control that are related to the dependent variable of interest.

In a later section we provide a series of robustness checks in which we vary the timing restriction on our measure of voucher competition in part to assess whether nonrandom private school acceptance of McKay vouchers is likely to influence our results. However, it is also helpful to provide a general description of the public schools around which voucher-accepting private schools are locating so that we can consider the likely direction and potential magnitude of any such bias.

We aggregate our student-year panel data set to the school-year level and run a series of pooled ordinary least squares (OLS) regressions. The regressions are exploratory and meant to illuminate the relationship between demographic and prior achievement variables and the number of private schools within 5 miles of a particular public school in a given year. Formally, the regression takes the form,

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$$Exp_{st} = \beta_0 + \beta_1 X_{st} + \beta_2 grade_{st} + \lambda_t + \kappa_{st} District + \varepsilon_{st}, \quad (4)$$

where s represents the public school and t the year; Exp is the number of private schools within a 5-mile radius; X is a vector of descriptive characteristics about the school; grade is a vector of the percentage of a school's students in a particular grade level; λ is a fixed effect for the year; District is an indicator for the school's district, which in Florida is equivalent to a fixed effect for the county and is used to partially account for urbanicity; and ε is a stochastic term that is clustered by school.

This simple regression framework is not meant to provide any causal analysis but rather to show the extent and direction that observed school characteristics of interest are related to our measure of a public school's exposure to vouchers. If public school exposure to McKay competition were random, then we would expect each manifestation of β_1 to be statistically indistinguishable from zero.

The results of the regressions taking a variety of forms are reported in Table 2. As expected, we find several statistically significant coefficients, which illustrates that public school exposure to competing private schools is nonrandom. The number of McKay-accepting private schools within 5 miles of a public school is negatively correlated with the average math and reading test scores for students within the public school. Furthermore, McKay-accepting private schools are more plentiful near public schools that serve higher percentages of students who are African American or are eligible for free or reduced-price lunch.[12]

That schools serving generally lower performing and more disadvantaged populations tend to be surrounded by more private competitors suggests nonrandom introduction of private schools should lead our estimates to understate the influence of additional exposure to McKay competition on student test scores. Furthermore, since lower performing students are more likely to be diagnosed as disabled than are high-performing students, the direction of any bias from nonrandom exposure to McKay competition will also tend to understate the theorized negative relationship between voucher competition and the likelihood that a child is diagnosed as SLD.

The fact that a public school's exposure to competing schools is nonrandom is concerning for estimation. We account for potential bias as the result of nonrandom exposure to private school competition by taking advantage of the panel nature of the data set. Our primary models include a fixed effect for each match between a student and a school. Use of these so called "spell effects" controls for unobserved time-invariant factors at both the school and student levels that are related to the dependent variable of interest (Abowd, Kramarz, & Margolis, 1999; Andrews, Schank, & Upward, 2004). Other recent articles that utilize the spell effect approach to evaluate public school responses to competition from school choice policies include Sass (2005), Bifulco and Ladd (2006), and Booker et al. (2008). For completeness, we also report the results of models that account for fixed effects at either the student or the school level. Depending on the level of fixed effect, estimates are based on within-student and/or within-school comparisons.

Data

We utilize a rich administrative data set supplied by the Florida Department of Education. The data set includes test score and demographic information for the universe of test-taking public school students in Florida in Grades 3 through 10 in school years 2000–2001 through 2004–2005. The data set has a unique student identifier that is used to track students over time.

We use student test scores on the Florida Comprehensive Assessment Test in both math and reading as our measure of student academic proficiency. Test scores are reported according to a vertical scale, meaning that identical scores on the exam should represent the same level of proficiency regardless of the grade level of the test.

Along with demographic information, the data set contains an identifier for whether the child has an IEP and the type of disability. We flag student-year observations where the student is listed as having an SLD. Students are said to have been newly diagnosed as SLD if their records indicate that they have such an IEP in a given year but did not have the SLD status in the prior year. We remove from the data set students who have an IEP but have a disability other than an SLD.

The Florida Department of Education also provided us with the names and addresses of private schools that made themselves eligible to receive McKay vouchers for each year from 2001–2002 through 2004–2005. We then used GIS software to map these and each public

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TABLE 2
Correlation Between Voucher Competition and Observed Student Characteristics

Average prior math score	–0.00714***					–0.00297***
	[–11.66]					[–2.734]
Average prior reading score		–0.00491***				0.00338***
		[–9.895]				[3.866]
Percentage Asian			3.248			3.81
			[0.887]			[0.966]
Percentage African American			5.788***			5.255***
			[17.43]			[11.69]
Percentage Hispanic			1.056*			–0.97
			[1.890]			[–1.157]
Percentage Indian			–9.203			–8.751
			[–1.436]			[–1.384]
Percentage multiple race			1.347			3.029
			[0.519]			[1.086]
Percentage eligible for free or reduced lunch				3.654***		1.022**
				[12.81]		[2.525]
Percentage limited English proficiency					–0.31	2.596***
					[–0.487]	[2.752]
Percentage male						0.722
						[1.225]
District fixed effect	√	√	√	√	√	√
Schools	3,168	3,167	3,190	3,190	3,190	3,167
Observations	11,797	11,799	11,897	11,897	11,897	11,795
R^2	.539	.534	.563	.541	.52	.568

Note. Dependent variable in all models is the number of private schools eligible to receive McKay vouchers within a 5-mile radius of the public school in a given year. Models estimated with ordinary least squares. *t*-statistics based on standard errors clustered by school are in brackets.
*$p < .10$. **$p < .05$. ***$p < .01$.

elementary school in the state by year to count the number of McKay-accepting private schools within a 5-mile radius of each public school.

The two types of analyses we conduct are subject to particular restrictions and thus use different samples of students, which we discuss in each respective section. Accordingly, we also provide descriptive statistics in the analysis sections.

Estimating the Relationship Between McKay Competition and SLD Diagnosis

In this section we measure whether the availability of McKay-receiving private school options is related to the probability that a regular enrollment student is newly diagnosed as having an SLD. To focus entirely on new diagnoses, we limit our panel data set to include only students who were not identified as disabled in any way in the prior year.[13] We do this because, unsurprisingly, in preliminary estimations we found that prior diagnosis of a disability is nearly a perfect predictor of a child having the same diagnosis in the next year. Thus, we would not expect that a policy change like McKay would have an impact on the probability that an already diagnosed child remains diagnosed.

Another reason to focus only on new diagnoses is to account for the possibility that parents of disabled students might move into areas that have greater availability of private schooling options where they can use McKay vouchers. If such a phenomenon exists, then including already diagnosed students in an analysis might lead us to mistakenly identify a seemingly increased probability that a student within a school is diagnosed as disabled as driven by the school's behavior rather than the parent's sorting into those schools.

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TABLE 3
Students in Sample Newly Diagnosed as Specific Learning Disability (SLD) by Grade

	Grade 4	Grade 5	Grade 6	Total
Grade-level entrants not previously diagnosed SLD	572,416	576,108	599,476	1,748,000
Diagnosed SLD	9,002	5,537	2,476	17,015
Percentage diagnosed SLD	1.6	1.0	0.4	1.0
Number of students in sample				942,181
Percentage of sample students identified as SLD by Grade 6				1.8

Ideally, we would follow students from the beginning of their public school careers, as early as preschool. However, since our data come from administrative information linked to the state's testing system, we are unable to observe students prior to the third grade. Our use of a lagged test score means that we are also unable to use students in the estimation prior to the fourth grade.[14] This is problematic since the majority of SLD diagnoses occur before the grade levels we observe. However, as Table 3 shows, there are a meaningful number of new SLD diagnoses in the fourth through sixth grades. About 1.6% of students who enter the fourth grade without having been diagnosed as SLD are so diagnosed by the end of the school year, and this decreases to about 0.4% of undiagnosed students in the sixth grade. In all, about 1% of fourth through sixth grade students are newly identified as disabled during these years.

Although we would prefer to include earlier grade levels, we argue that the available data do allow for sufficient variation in the identification of SLD for us to proceed. However, we caution that the relationship between SLD diagnosis and McKay exposure might be different in the earlier grades not covered in our analysis.

Descriptive statistics for our analysis of the relationship between competition from McKay and the probability that a child is diagnosed as learning disabled are reported in Table 4.

We estimate a model taking the form,

$$SLD_{ist} = \beta_0 + \beta_1 X_{st} + \beta_2 Exp_{ist} + \Psi_{is} + \theta_t + \varepsilon_{ist} + \varepsilon_s , \quad (5)$$

where SLD is an indicator that equals 1 if student i enrolled in school s is identified as SLD by the end of year t and zero otherwise; X is a vector of time-varying observed characteristics for the student, which includes grade level and the student's test scores in both math and reading from the previous year; Exp represents the competitive threat from the McKay program, which we measure as the number of McKay-accepting private schools within a 5-mile radius of the public school; θ is a fixed effect for the year; ψ is a student-school spell fixed effect; ε is a stochastic term clustered by school; and $\beta_0 - \beta_2$ are parameters to be estimated.

We estimate Equation 5 via OLS, which results in a linear probability model. For the classical reasons, the limitations of SLD as a binary variable suggest that a method such as probit is preferred. However, it is computationally burdensome to include a large number of fixed effects in probit models using conventional software.

The results from estimating Equation 5 are reported in Table 5. The table only reports the estimated coefficient on our independent variable of interest. We report models that account for varying levels of fixed effects, at the school, student, or school-student spell level. The models that include only a school-level fixed effect also utilize observed time-invariant student characteristics as regressors. We also report models that expand our definition of exposure to McKay to represent the number of voucher-accepting private schools within a 10-mile radius of a public school during a particular year.

All models find a statistically significant negative relationship between the number of McKay-accepting private schools within a 5- or 10-mile radius of a student's public school and the probability that he or she is newly identified as SLD. We take as our primary estimate the results reported in the table's third column, which utilize the within 5 miles definition of competition and include a school-student spell effect. That model

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TABLE 4
Summary Statistics for Models Evaluating Effect of McKay on Probability of Specific Learning Disability (SLD) Diagnosis

	M	*SD*
Diagnosed SLD during sample period	0.01	0.10
Year 2001–2002	0.24	0.43
Year 2002–2003	0.25	0.43
Year 2003–2004	0.25	0.43
Year 2004–2005	0.25	0.43
Grade 4	0.33	0.47
Grade 5	0.33	0.47
Grade 6	0.34	0.47
Not limited English proficient	0.82	0.38
Male	0.48	0.50
Asian	0.02	0.14
African American	0.23	0.42
Hispanic	0.22	0.41
Indian	0.00	0.05
Multiple race	0.02	0.15
White	0.50	0.50
Not free or reduced-price lunch	0.45	0.50
Prior math score	1505.84	276.92
Prior reading score	1504.35	338.39
McKay-accepting schools within 5 miles	5.69	5.88
McKay-accepting schools within 10 miles	16.57	15.74

estimates that the addition of one more voucher-accepting private school within a 5-mile radius of a public school is related to a decrease in the probability that a child is identified as learning disabled by about 0.0165 percentage points. Our large number of both students and schools provides confidence that our estimates are able to measure such small effects accurately.

Expanding the definition of competition to include voucher-accepting private schools that are within 10 miles of a public school yields estimates that are similar in direction and significance but are smaller in magnitude than those that result from the analysis of McKay competition within 5 miles of the public school. That result is expected given that the number of McKay schools within 5 miles is highly correlated with the number of such schools within 10 miles, though we might expect that the addition of schools further away might impose a smaller competitive effect.

The size of the effect is perhaps more substantial than it first appears. As shown in Table 1, in 2004–2005 the last year for which we have such data, there were seven McKay-accepting private schools within a 5-mile radius for the average public school in the state. Thus, our estimate translates into about a 12% reduction in the probability that a fourth through sixth grade student in a school with average 2004–2005 McKay exposure was identified as SLD.

Estimating the Relationship Between McKay and Public School Achievement

We now turn to measuring the influence of competition from the McKay program on public school quality. For this analysis we expand our previous sample to include all Florida public school students in Grades 3 through 10 whose test scores we observe and who did not have a disability classification other than SLD.

Our primary estimation procedure utilizes a series of fixed effects to account for student, school, time, and grade-level factors that are important to a student's test score. This model takes the form,

$$y_{ist} = \alpha_1 + \alpha_2 SLD + \alpha_3 grade_{ist} + \alpha_4 Exp_{ist} + \delta_t + \pi_{is} + \mu_{ist}, \quad (6)$$

where y is student i's test score in school s at the end of year t; SLD equals one if the student is classified as having an SLD and zero otherwise; grade is an indicator for the student's grade level; δ is a fixed effect for the year; π is a school-student spell fixed effect; Exp represents our measure for voucher competition; and μ is a stochastic term clustered by school. As in the prior section, we also estimate models that vary the fixed effect to be at the school or student level.

Models that utilize only a school fixed effect include a vector of observed time-invariant student characteristics. Furthermore, to account for unobserved student heterogeneity, the school fixed effect model also includes as a regressor the student's test score at the end of the prior year, which forces us to exclude third grade students. Though we do not report the results here, we tested whether the exclusion of third grade students could explain any difference between the models that include a school fixed effect and those that include more fine fixed

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TABLE 5

Regression Results—Measuring the Relationship Between McKay Competition and Probability a Student Is Diagnosed as Specific Learning Disability (SLD)

McKay-accepting schools within 5 miles	–0.000189**	–0.000140***	–0.000165***			
	[–2.376]	[–2.951]	[–3.178]			
McKay-accepting schools within 10 miles				–6.40e-05**	–0.000107***	–0.000128***
				[–1.987]	[–4.173]	[–4.317]
Time-invariant student characteristics	√			√		
Prior student test scores	√	√	√	√	√	√
Grade fixed effect	√	√	√	√	√	√
Year fixed effect	√	√	√	√	√	√
School fixed effect	√			√		
Student fixed effect		√			√	
Student-school spell effect			√			√
Schools	2,584	2,584	2,584	2,584	2,584	2,584
Students		942,181			942,181	
Student-school spells			960,701			960,701
Observations	1,748,000	1,748,000	1,748,000	1,748,000	1,748,000	1,748,000
R^2	.028	.842	.844	.028	.842	.844

Note. Dependent variable in all models is an indicator for whether the student is newly diagnosed as SLD. Regressions also control student's prior math and reading test scores. Time-invariant student characteristics include student race/ethnicity, free or reduced-price lunch eligibility, and whether English is the student's second language. *t*-statistics resulting from robust standard errors clustered by school are in brackets.

$^{**}p < .05$. $^{***}p < .01$.

effects by running regressions that utilized a student or school-student spell effect but excluded third grade students. Results were very similar to our primary models utilizing those respective effects that include third grade students.

Descriptive statistics for the analyses evaluating the impact of McKay competition on student proficiency in public schools are found in Table 6.

Before we report the results from estimating Equation 6, there are two issues related to nonrandom selection that are worth considering. The first potential problem is that SLD students almost certainly use McKay vouchers nonrandomly. Second, our previous finding that exposure to the McKay program leads to a decrease in the probability that a student is diagnosed as having an SLD is also potentially problematic since the classification of fewer marginal students will tend to decrease the average proficiency of both regular enrollment and special education students. We rely primarily on our use of fixed effects to provide within-student and within-school estimates to account for these and other potential selection issues.

The results from estimating Equation 6 to evaluate student math proficiency are found in Table 7. We again report the results from models that vary the level of fixed effect and the spatial definition of voucher competition. In addition, to test our model's prediction that special education vouchers could influence the proficiency of both disabled and regular enrollment students, we report the results of models in which the data set is restricted to include only students who have been identified as having an SLD and only students who have not been diagnosed with a disability.

The top set of results report the estimates from models that utilize the full sample of students. The models that include only a school-level fixed effect find no significant relationship between McKay competition and student math proficiency. However, our preferred models that account for unobserved student heterogeneity by including a student

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TABLE 6
Summary Statistics for Models Evaluating Effect of McKay on Public School Student Proficiency

	M	*SD*
Math score	1769.00	274.23
Reading score	1742.41	337.49
Previous math score	1668.66	308.30
Previous reading score	1642.34	369.52
Not limited English proficient	0.82	0.38
Male	0.49	0.50
White	0.51	0.50
Asian	0.02	0.14
African American	0.23	0.42
Hispanic	0.21	0.41
Indian	0.00	0.05
Multiple-race	0.02	0.13
Not free or reduced-price lunch	0.51	0.50
Year 2001–2002	0.24	0.42
Year 2002–2003	0.25	0.43
Year 2003–2004	0.25	0.44
Year 2004–2005	0.26	0.44
Grade 4	0.14	0.34
Grade 5	0.14	0.35
Grade 6	0.15	0.35
Grade 7	0.15	0.35
Grade 8	0.15	0.35
Grade 9	0.15	0.36
Grade 10	0.14	0.35
Specific learning disability	0.09	0.29
McKay-accepting schools within 5 miles	5.80	5.98

or school-student spell effect find a significant positive relationship between the level of voucher competition and student math proficiency.

The second set of regressions finds no significant relationship between the number of voucher-accepting private schools within 5 miles and the academic achievement of SLD students. However, when we expand the definition of competition to the number of voucher-accepting private schools within 10 miles of a public school we find a significant relationship that is similar in size to the finding from the full sample.

Finally, the third set of results provides evidence that competition from McKay was related to academic improvement for regular enrollment students. Recall that our theoretical foundation suggests that regular enrollment students could benefit from the influence that special education vouchers have on the school's peer composition and productivity improvements in response to competition.

Table 8 reports the results of our estimates for student reading proficiency. The results from reading are similar to those from our math analysis in direction and significance. It is somewhat concerning that models that utilize only a school fixed effect find a significant negative relationship between voucher competition and reading proficiency. However, the full sample estimates that account for all unobserved student factors by incorporating a student or student-school spell fixed effect find a significant positive relationship between voucher exposure and student reading achievement.

As in the math analysis, we find a significant relationship between the reading achievement of SLD students and exposure to McKay only when we expand our measure of competition from the program to include schools within a 10-mile radius of a public school. We also again find a significant positive relationship between competition from vouchers and the reading proficiency of students who have not been diagnosed with a disability.

We can better understand the magnitude of our estimates by converting them into standard deviation units. The descriptive statistics show that the standard deviations on the math and reading exams for students in our sample were 274 and 337, respectively. Furthermore, in 2004–2005, the final year we observe, there was an average of seven voucher-accepting private schools within 5 miles of a Florida public school. Thus, our full sample results from the model that utilizes school-student spell fixed effects and the within 5 miles definition finds that being in a public school surrounded by the average number of McKay-accepting private schools was related to an increase in academic proficiency of about 0.01 standard deviations in both math and reading. The positive but very mild competitive effect is consistent with what has been found in previous research evaluating more conventional school choice policies.

Testing the Timing Restriction for McKay Competition

Our results are intriguing and are generally consistent with our theoretical predictions. However, we might be concerned that identification relies on the variation in the timing and location of private schools that make themselves eligible to

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TABLE 7

Regression Results—Measuring the Relationship Between McKay and Student Math Proficiency in Public Schools

			All students			
McKay-accepting schools within 5 miles	–0.0219	0.328***	0.371***			
	[–0.184]	[3.061]	[3.211]			
McKay-accepting schools within 10 miles				–0.00813	0.330***	0.372***
				[–0.160]	[6.501]	[6.421]
Schools	3,152	3,190	3,190	3,152	3,190	3,190
Students		2,215,689			2,215,689	
Student-school spells			2,281,936			2,281,936
Observations	4,458,534	5,715,183	5,715,183	4,458,534	5,715,183	5,715,183
R^2	.792	.923	.924	.792	.923	.924
			Specific learning disability students			
McKay-accepting schools within 5 miles	0.0792	0.056	0.0708			
	[0.314]	[0.299]	[0.355]			
McKay-accepting schools within 10 miles				0.161	0.292***	0.307***
				[1.514]	[3.281]	[3.152]
Schools	3,081	3,122	3,122	3,081	3,122	3,122
Students		203,492			203,492	
Student-school spells			210,140			210,140
Observations	404,583	514,694	514,694	404,583	514,694	514,694
R^2	.684	.88	.883	.684	.88	.883
			Regular enrollment students			
McKay-accepting schools within 5 miles	–0.0397	0.383***	0.428***			
	[–0.323]	[3.491]	[3.625]			
McKay-accepting schools within 10 miles				–0.0278	0.358***	0.402***
				[–0.528]	[6.883]	[6.776]
Schools	3,134	3,181	3,181	3,134	3,181	3,181
Students		2,036,168			2,036,168	
Student-School Spells			2,095,317			2,095,317
Observations	4,053,951	5,200,489	5,200,489	4,053,951	5,200,489	5,200,489
R^2	.792	.926	.927	.792	.926	.927
Time-invariant student characteristics	√			√		
Prior student test scores	√			√		
Grade fixed effect	√	√	√	√	√	√
Year fixed effect	√	√	√	√	√	√
School fixed effect	√			√		
Student fixed effect		√			√	
Student-school spell effect			√			√

Note. Dependent variable is the student's math test score. Time-invariant student characteristics include student race/ethnicity, free or reduced-price lunch eligibility, and whether English is the student's second language. *t*-statistics resulting from robust standard errors clustered by school are in brackets.

***$p < .01$.

accept McKay vouchers. In this section we test the robustness of this identification strategy by estimating models that vary the timing of McKay exposure to represent either past or future exposure to voucher competitors.

We first test for a continuous response to McKay competition by estimating models that lag the measure of voucher exposure to represent the number of voucher-accepting private schools within 5 miles of the public school during the

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TABLE 8

Regression Results—Measuring the Relationship Between McKay and Student Reading Proficiency in Public Schools

			All students			
McKay-accepting schools within 5 miles	–1.009***	0.538***	0.618***			
	[–7.352]	[3.792]	[4.083]			
McKay-accepting schools within 10 miles				–0.491***	0.453***	0.533***
				[–8.577]	[7.350]	[7.592]
Schools	3,152	3,190	3,190	3,152	3,190	3,190
Students		2,215,689			2,215,689	
Student-school spells			2,281,936			2,281,936
Observations	4,458,534	5,715,183	5,715,183	4,458,534	5,715,183	5,715,183
R^2	.715	.895	.896	.715	.895	.896
			Specific learning disability students			
McKay-accepting schools within 5 miles	0.0703	0.401*	0.31			
	[0.210]	[1.800]	[1.292]			
McKay-accepting schools within 10 miles				0.101	0.448***	0.450***
				[0.731]	[4.383]	[3.963]
Schools	3,081	3,122	3,122	3,081	3,122	3,122
Students		203,492			203,492	
Student-school spells			210,140			210,140
Observations	404,583	514,694	514,694	404,583	514,694	514,694
R^2	.624	.861	.864	.624	.861	.864
			Regular enrollment students			
McKay-accepting schools within 5 miles	–1.122***	0.597***	0.695***			
	[–8.223]	[4.114]	[4.512]			
McKay-accepting schools within 10 miles				–0.548***	0.497***	0.586***
				[–9.657]	[7.984]	[8.288]
Schools	3,134	3,181	3,181	3,134	3,181	3,181
Students		2,036,168			2,036,168	
Student-school spells			2,095,317			2,095,317
Observations	4,053,951	5,200,489	5,200,489	4,053,951	5,200,489	5,200,489
R^2	.697	.892	.894	.697	.892	.894
Time-invariant student characteristics	√			√		
Prior student test scores	√			√		
Grade fixed effect	√	√	√	√	√	√
Year fixed effect	√	√	√	√	√	√
School fixed effect	√			√		
Student fixed effect		√			√	
Student-school spell effect			√			√

Note. Dependent variable is the student's reading test score. Time-invariant student characteristics include student race/ethnicity, free or reduced-price lunch eligibility, and whether English is the student's second language. *t*-statistics resulting from robust standard errors clustered by school are in brackets.
*$p < .10$. ***$p < .01$.

previous school year. Formally, we estimate models taking the following forms:

$$SLD_{ist} = \beta_0 + \beta_1 X_{ist} + \beta_2 Exp_{st-1} + \Psi_{is} + \theta_t + \varepsilon_{ist} + \varepsilon_s \quad (7a)$$

$$y_{ist} = \alpha_1 + \alpha_2 SLD + \gamma\, grade_{ist} + \delta_t + \pi_{is} + \alpha_3 Exp_{st-1} + \mu_{ist} \quad (7b)$$

Note that Equations 7a and 7b are identical to Models 5 and 6, respectively, except that the Exp

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variable now represents the number of voucher-accepting private schools within a 5-mile radius during the previous school year.

To be clear, because it is the school (not the student) that competes with McKay, the Exp variable is lagged at the school level. That is, for a given student-year observation, the variable lists the number of private competitors that surrounded the student's current school in the previous year. Thus, if the student attended school A during year t-1 and school B during year t, then the student's year t observation would include as the lagged exposure variable the number of private schools within 5 miles of school B during school year t-1.

We also test the timing restriction by altering our models for estimation to account for future competition from voucher-accepting private schools. A significant relationship between SLD diagnosis or test scores and future McKay competition could come about as the result of a time trend for which our primary models fail to account. Alternatively, it is possible that public schools anticipate voucher competition from nearby private schools that have not yet made themselves eligible to receive a voucher.

We estimate models where the measure of McKay exposure is the number of private schools within a 5-mile radius of a public school that were eligible to accept vouchers the next year or two years later. Formally,

$$SLD_{ist} = \beta_0 + \beta_1 X_{ist} + \beta_2 Exp_{st+1} + \Psi_{is} + \theta_t + \varepsilon_{ist} + \varepsilon_s \quad (8a)$$

$$SLD_{ist} = \beta_0 + \beta_1 X_{ist} + \beta_2 Exp_{st+2} + \Psi_{is} + \theta_t + \varepsilon_{ist} + \varepsilon_s \quad (8b)$$

$$y_{ist} = \alpha_1 + \alpha_2 SLD + \gamma\, grade_{ist} + \delta_t + \pi_{is} + \alpha_3 Exp_{st+1} + \mu_{ist} \quad (9a)$$

$$y_{ist} = \alpha_1 + \alpha_2 SLD + \gamma\, grade_{ist} + \delta_t + \pi_{is} + \alpha_3 Exp_{st+2} + \mu_{ist} \quad (9b)$$

where, again, Equations 8 and 9 are identical to Equations 5 and 6, respectively, except for the timing of the Exp variable.

The analysis of the relationship between our dependent variables of interest and future competition from McKay can in part be thought of as a test for the extent to which nonrandom sorting of voucher-accepting private schools influences our results. If future exposure to voucher-accepting private schools has a similar influence on SLD diagnosis or student proficiency as does contemporaneous or lagged exposure to the program then we would worry that our primary models are picking up unobserved factors that are related the dependent variable as well as our measure of voucher competition.

Because of data limitations, the analysis that evaluates the influence of lagged McKay exposure utilizes only observations from school years 2002–2003 through 2004–2005. Similarly, the analysis of McKay exposure 1 year in the future utilizes observations from 2001–2002 through 2003–2004, and the analysis of exposure 2 years later utilizes observations from 2001–2002 and 2002–2003.

Table 9 reports the results of each of the above discussed robustness checks for the analysis evaluating the relationship between McKay competition and the probability that a student is newly diagnosed as having an SLD. For space considerations, we include the results of each regression in a single table. Each cell in the table represents the coefficient estimate and *t*-statistic resulting from one of the nine reported regressions. Each of the regressions controls for the same student and school characteristics as reported in its respective analysis reported in our main results section.

Our assumption of a contemporaneous competitive effect appears valid in the case of our evaluation of SLD diagnosis. None of the models that utilize a student or student-school spell fixed effect finds a significant relationship with SLD diagnosis and alternative timing of the exposure variable. Recall from our primary results (reported in Table 5) that each of our models found a statistically significant negative relationship between SLD diagnosis and the number of nearby voucher-accepting private schools in the current year.

The results from our robustness checks for the test score evaluations, shown in Table 10, are also intriguing. We again provide the results of several different regressions in a single table. Each cell represents the coefficient estimate and *t*-statistic resulting from a different regression. The table reports coefficient estimates from 54 regressions in total (three variations in the timing of competition, three levels of fixed effects, two subjects, and three different samples).

We first consider the results for the robustness checks that lag our measure of voucher competition by one year. All models find a significant positive relationship between this year's student proficiency and the voucher competition that the school faced last year. In fact, the coefficient estimate for lagged

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TABLE 9

Robustness Test Altering Timing of McKay Competition—Analysis of Specific Learning Disability (SLD) Diagnosis

Lagged McKay-accepting schools within 5 miles	3.57e-05	–5.09e-05	–7.05e-05
	[0.454]	[–0.771]	[–0.981]
Future (1 year) McKay-accepting schools within 5 miles	–0.00015	–1.26e-05	–2.58e-05
	[–1.130]	[–0.231]	[–0.435]
Future (2 years) McKay-accepting schools within 5 miles	0.000642***	9.27e-05	0.000104
	[2.917]	[1.281]	[1.370]
Time-invariant student characteristics	√		
Prior student test scores	√	√	√
Grade fixed effect	√	√	√
Year fixed effect	√	√	√
School fixed effect	√		
Student fixed effect		√	
Student-school spell effect			√

Note. Each cell represents the estimates from an independent regression (nine regressions in total). Dependent variable in all models is an indicator for whether the student is newly diagnosed as SLD. Regressions also control for student's prior math and reading test scores. Time-invariant student characteristics include student race/ethnicity, free or reduced-price lunch eligibility, and whether English is the student's second language. *t*-statistics resulting from robust standard errors clustered by school are in brackets.
***$p < .01$.

competition is consistently more than twice the size than was the case for the respective evaluation of contemporaneous competition reported in Tables 7 and 8. We interpret these results as evidence that the influence of voucher competition on school productivity could increase over time. Our theory would suggest that this continuing effect could occur as more students utilize the voucher—and thus altering peer composition within the school—or as the public school makes efficiency improvements to compete for enrollment.

The results from our analysis of the influence of a school's future voucher exposure and its current students are not as clean as the similar test for our evaluation of SLD diagnosis but appear to generally justify our estimation procedure, at least in math. We find no significant relationship between student math proficiency and the number of nearby private schools that will accept vouchers in the next year. However, we find a significant negative relationship between math proficiency and the competition that a student's school faces 2 years in the future. For reading, we find a significant positive relationship between proficiency and the school's next year's competition from vouchers, and the coefficient is about three fifths the size as the findings from the main contemporaneous model. We find no significant relationship to voucher competition 2 years later. Thus, it appears that a time trend could significantly influence our primary results in reading, but we find no such evidence of a time trend in math.

An important limitation of the above robustness tests is that the number of years for which we have information on the number of nearby voucher-accepting private schools forces us to utilize different samples than our primary analyses. We test whether the differential results for future and contemporaneous competition from McKay are related to the restrictions on the year of observations utilized in the analyses by running our primary models using the same year restrictions as in the robustness tests. That is, we ran our analyses evaluating the relationship between the number of nearby voucher-accepting private schools in the current year using only observations for students in the 2001–2002 through 2003–2004 and then from the 2001–2002 and 2002–2003 school years. For this test, we ran models only on our full sample of students.

Table 11 reports the results from analyses of contemporaneous McKay competition on SLD diagnosis and test score performance using only observations from the restricted sample years. Each cell represents coefficient estimates and *t*-statistics for an independently run regression. If the exclusion of sample years in our robustness tests is unimportant, then we would expect the coefficient estimates reported in Table 11 to be similar to those in the respective analysis reported in our main results section in Tables 5, 7, and 8.

The results indicate that the difference between our main results for contemporaneous McKay competition and the estimated effect

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TABLE 10

Robustness Test Altering Timing of McKay Competition—Student Proficiency Analyses

	Mathematics			Reading		
	All students					
Lagged McKay-accepting schools within 5 miles	0.623***	0.717***	0.800***	0.241	0.845***	0.958***
	[4.743]	[5.591]	[5.925]	[1.096]	[5.174]	[5.666]
Future (1 year) McKay-accepting schools within 5 miles	–0.775***	–0.00797	–0.0308	–1.784***	0.333***	0.371***
	[–3.490]	[–0.0774]	[–0.271]	[–7.270]	[2.687]	[2.724]
Future (2 years) McKay-accepting schools within 5 miles	–0.516	–0.319**	–0.406**	–0.209	–0.116	–0.161
	[–0.910]	[–2.259]	[–2.559]	[–0.349]	[–0.739]	[–0.926]
	Specific learning disability students					
Lagged McKay-accepting schools within 5 miles	1.640***	1.007***	0.915***	1.414***	0.856***	0.858***
	[4.589]	[3.831]	[3.692]	[3.094]	[2.969]	[2.808]
Future (1 year) McKay-accepting schools within 5 miles	–0.850*	–0.422	–0.388	–1.354**	0.121	–0.0481
	[–1.671]	[–1.614]	[–1.614]	[–2.287]	[0.437]	[–0.158]
Future (2 years) McKay-accepting schools within 5 miles	0.0983	–0.734**	–0.950**	0.867	0.115	–0.0741
	[0.0789]	[–2.035]	[–2.435]	[0.586]	[0.294]	[–0.174]
	Regular enrollment students					
Lagged McKay-accepting schools within 5 miles	0.520***	0.810***	0.728***	0.116	0.897***	1.020***
	[4.065]	[5.932]	[5.628]	[0.535]	[5.367]	[5.892]
Future (1 year) McKay-accepting schools within 5 miles	–0.769***	0.037	0.057	–1.805***	0.383***	0.449***
	[–3.423]	[0.322]	[0.546]	[–7.253]	[3.059]	[3.269]
Future (2 years) McKay-accepting schools within 5 miles	–0.586	–0.283**	–0.356**	–0.396	–0.156	–0.186
	[–1.027]	[–1.989]	[–2.235]	[–0.665]	[–0.968]	[–1.035]
Time-invariant student characteristics	√			√		
Prior student test scores	√			√		
Grade fixed effect	√	√	√	√	√	√
Year fixed effect	√	√	√	√	√	√
School fixed effect	√			√		
Student fixed effect		√			√	
Student-school spell effect			√			√

Note. Each cell represents the estimates from an independent regression (54 regressions in total). Dependent variable is the student's math or reading test score. Time-invariant student characteristics include student race/ethnicity, free or reduced-price lunch eligibility, and whether English is the student's second language. *t*-statistics resulting from robust standard errors clustered by school are in brackets.

*$p < .10$. **$p < .05$. ***$p < .01$.

of competition one year in the future does not appear to be primarily determined by the differences in the years of observations utilized. Both the size and significance of the coefficient estimates reported in Table 11 are similar to those that resulted from our primary estimations. However, the test provides some reason to worry that the results from the analysis of the influence of McKay competition 2 years in the future could be in part the result of the restricted sample used in the robustness test. The size and significance of the coefficients on contemporary voucher competition for the reading analysis when we use the restricted sample are very similar to those reported in our main results. We find an insignificant relationship between contemporaneous McKay competition and math scores as well as SLD diagnosis. Thus, we should place some confidence in our robustness check looking at the influence of McKay competition one year in the future, but we should be cautious about putting too much emphasis on the test looking at competition 2 years in the future.

Summary and Conclusion

Understanding the effects of school choice programs on traditional public schools requires a careful examination of how different design

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TABLE 11

Analysis of Contemporaneous McKay Exposure Using Samples Restricted to Years of Respective Robustness Tests

Dependent variable	One year in future sample			Two years in future sample		
Specific learning disability diagnosis	–0.000321*** [–3.091]	–0.000213*** [–2.816]	–0.000238*** [–2.890]	0.000184 [1.443]	1.55E-05 [0.149]	2.23E-05 [0.204]
Math test score	–0.338** [–2.348]	0.414*** [3.337]	0.437*** [3.273]	–0.967*** [–3.520]	0.247 [1.189]	0.262 [1.170]
Reading test score	–1.375*** [–9.122]	0.588*** [3.982]	0.647*** [4.060]	–1.908*** [–6.002]	0.483* [1.942]	0.517* [1.925]
Time-invariant student characteristics	√			√		
Prior student test scores	√			√		
School fixed effect	√			√		
Student fixed effect		√			√	
Student-school spell effect			√			√

Note. Each cell represents the estimates from an independent regression (18 regressions in total). Dependent variable utilized in the analysis is listed in the left-hand column. Models utilizing the "one year in future sample" utilize observations from the 2001–2002 through the 2003–2004 school years. Models utilizing the "two years in future sample" utilize observations from the 2001–2002 and 2002–2003 school years. Time-invariant student characteristics include student race/ethnicity, free or reduced-price lunch eligibility, and whether English is the student's second language. *t*-statistics resulting from robust standard errors clustered by school are in brackets.

*$p < .10$. **$p < .05$. ***$p < .01$.

features in those choice programs may alter the impact. Voucher programs for special education students differ significantly from other school choice programs and may produce substantially different effects. In addition, the growing number of special education voucher programs makes studying them important in its own right.

Using data from Florida's McKay Scholarship Program for Students with Disabilities, we find that offering special education vouchers to disabled students appears to reduce the likelihood that public schools will identify students as having an SLD. For students in fourth through sixth grade, being in a school with average exposure to the McKay program reduced the rate of being identified as SLD by about 12%. This finding was robust to multiple specifications of the model, including the inclusion of student fixed effects and different geographic measures of exposure to McKay.

The results on how McKay affects student achievement in traditional public schools are less robust and considerably smaller in size. Although the findings vary somewhat depending on model specification and sample examined, the results suggest that McKay tends to have a positive but very modest impact on math and reading performance of the students in public schools.

These results generally confirm the findings of earlier research. The reduction in SLD identifications related to McKay confirms earlier work that public schools engage in strategic diagnosis of subjectively identified disabilities in response to financial or testing pressures. Furthermore, the positive, but small, improvements in public school student achievement related to McKay competition are consistent with earlier research that finds a weak but usually positive relationship between school choice and public school performance.

The analyses presented here make a significant contribution by examining for the first time the effects of special education vouchers on public school diagnosis of disability and academic achievement. Although the McKay design yields results that are consistent with those of other choice programs and is the most common model for other special education voucher programs, it is still unknown whether other choice programs, for disabled or other students, would produce similar effects. Additional research can shed light on how differently designed choice programs may differ in their results.

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Notes

1. Relevant research reviewed by Gill and Booker includes evaluations of the influence of competition from charter schools on public school student achievement (Bettinger, 2005; Bifulco & Ladd, 2006; Booker, Gilpatric, Gronberg, & Jansen, 2008; Buddin & Zimmer, 2004; Hoxby, 2002; Sass, 2005) and the competitive effect of vouchers on public school achievement Greene and Winters, 2003; Greene and Winters, 2006; Chakrabarti, 2005; Figlio & Rouse, 2006; Hoxby, 2002; Hsieh & Urquiola, 2001; McEwan & Carnoy, 2000; West & Peterson, 2006).

2. See Florida Department of Education, Bureau of Exceptional Education and Student Services (n.d.).

3. See Florida Department of Education (2009).

4. See Florida Department of Education (2009).

5. See http://www.floridaschoolchoice.org/Information/McKay/files/Fast_Facts_McKay.pdf.

6. See http://www.slc.sevier.org/ldoutl.htm.

7. See http://idea.ed.gov/explore/view/p/,root,dynamic,TopicalBrief,23,

8. See Digest of Education Statistics (2009, Table 51).

9. See Digest of Education Statistics (2009, Table 50).

10. As nonprofit government organizations, public schools do not truly seek to maximize profit in the same way as do private firms. However, we utilize the profit-maximizing framework here because it is a useful tool to look at the school's incentive to maximize instructional revenues, and so on.

11. See Epple and Romano (1998, 2002), Nechyba (1999, 2000, 2003), and Caucutt (2001).

12. Both the sign and size of the coefficients are very similar if we restrict the model to include schools only during the final year included in the data set, the 2004–2005 school year.

13. Because of this restriction, once a student in our data set is identified as disabled he or she will then exit the sample.

14. Third grade students would have a prior test score if they were retained at the end of the prior year. However, we exclude such students because they are not representative of all third grade students.

References

Abowd, J., Kramarz, F., & Margolis, D. (1999). High-wage workers and high-wage firms. *Econometrica, 67,* 251–333.

Andrews, M. J., Schank, T., & Upward, R. (2004). *Practical estimation methods for linked employer-employee data.* Discussion Papers 29, Friedrich-Alexander-University Erlangen-Nuremberg, Chair of Labour and Regional Economics.

Bettinger, E. P. (2005). The effect of charter schools on charter students and public schools. *Economics of Education Review*, *24*, 133–147.

Bifulco, R., & Ladd, H. F. (2006). The impact of charter schools on student achievement: Evidence from North Carolina. *Journal of Education Finance and Policy*, *1*, 50–90.

Booker, K., Gilpatric, S. M., Gronberg, T., & Jansen, D. (2008). The effect of charter schools on traditional public school students in Texas: Are children who stay behind left behind? *Journal of Urban Economics*, *64*, 123–145.

Buddin, R., & Zimmer, R. (2004). *Is charter school competition in California improving the performance of traditional public schools?* Unpublished manuscript.

Caucutt, E. (2001). Peer group effects in applied general equilibrium. *Economic Theory*, *17*, 25–51.

Chakrabarti, R. (2005). *Impact of voucher design on public school performance: Evidence from Florida and Milwaukee voucher programs* (Working paper). Cambridge, MA: Harvard University.

Cullen, J. B. (2001). The impact of fiscal incentives on student disability rates. *Journal of Public Economics*, *87*, 1557–1589.

Cullen, J. B., & Reback, R. (2002). *Tinkering toward accolades: School gaming under a performance accountability system*. Unpublished manuscript.

Dhuey, E., & Lipscomb, S. (2008). *The effects of fiscal incentives in special education: Evidence from finance reform*. Unpublished manuscript.

Epple, D., & Romano, R. (1998). Competition between public and private schools, vouchers and peer group effects. *American Economic Review*, *88*, 33–62.

Epple, D., & Romano, R. (2002, November). *Educational vouchers and cream skimming* (NBER Working Paper No. 9354). Cambridge, MA: National Bureau of Economic Research.

Figlio, D. N., & Getzler, L. S. (2002). *Accountability, ability, and disability: Gaming the system* (Working Paper 9307). Cambridge, MA: National Bureau of Economic Research.

Figlio, D., & Rouse, C. E. (2006). Do accountability and voucher threats improve low-performing schools? *Journal of Public Economics*, *90*, 239–255.

Florida Department of Education. (2009). *John M. McKay Scholarship Program, June Quarterly Report, 2009*. Retrieved from http://www.floridaschoolchoice.org/Information/McKay/quarterly_reports/mckay_report_june2009.pdf

Florida Department of Education, Bureau of Exceptional Education and Student Services. (n.d.). *Students with disabilities enrollment, ages 6–21, 2008–09*. Retrieved from http://www.fldoe.org/ese/pdf/b-621.pdf

Gill, B., & Booker, K. (2008). School competition and student outcomes. In H. F. Ladd & E. B. Fiske (Eds.), *Handbook of research in education finance and policy* (pp. 183–202). New York, NY: Routledge.

Downloaded from http://eepa.aera.net at UNIV OF ARKANSAS on June 7, 2011

Greene, J. P., & Forster, G. (2002). *Effects of funding incentives on special education enrollment*. Manhattan Institute, Civic Report 32.

Greene, J. P., & Winters, M. A. (2003). *When schools compete: The effects of vouchers on Florida public school achievement*. Manhattan Institute.

Greene, J. P., & Winters, M. A. (2006). *An evaluation of the effect of D.C.'s voucher program on public school achievement and racial integration after one year*. Manhattan Institute.

Hoxby, C. M. (2002). *School choice and school productivity (Or could school choice be a tide that lifts all boats?)* (Working Paper 8873). Cambridge, MA: National Bureau of Economic Research.

Hsieh, C., & Urquiola, M. (2001, November). *When schools compete, how do they compete? An assessment of Chile's Nationwide School Voucher Program*. Paper presented at the UCLA/RAND Joint Labor and Population Workshop, Santa Monica, CA.

Jacob, B. (2005). Accountability, incentives and behavior: Evidence from school reform in Chicago. *Journal of Public Economics*, *89*, 761–796.

Kwak, S. (2008). *The impact of intergovernmental incentives on disability rates and special education spending*. Unpublished manuscript.

Macmillan, D. L., & Siperstein, G. N. (2001, August). *Learning disabilities as operationally defined by schools*. Paper presented at the 2001 LD Summit: Building a Foundation for the Future, Washington, DC.

Mahitivanichcha, K., & Parrish, T. (2005). The implications of fiscal incentives on identification rates and placement in special education: Formulas for influencing best practice. *Journal of Education Finance*, *31*, 1–22.

McEwan, P. J., & Carnoy, M. (2000). The effectiveness and efficiency of private schools in Chile's voucher system. *Educational Evaluation and Policy Analysis*, *22*, 213–239.

Nechyba, T. (1999). School finance induced migration patterns: The impact of private school vouchers. *Journal of Public Economic Theory*, *1*, 5–50.

Nechyba, T. (2000). Mobility, targeting and private school vouchers. *American Economic Review*, *90*, 130–146.

Nechyba, T. (2003). Introducing school choice into multidistrict public school systems. In C. Hoxby (Ed.), *The economics of school choice* (pp. 145–194). Cambridge, MA: National Bureau of Economic Research.

Sass, T. R. (2005). *Charter schools and student achievement in Florida*. Unpublished manuscript.

Shepard, L. A., Smith, M. L., & Vojir, C. P. (1983). Characteristics of pupils identified as learning disabled. *American Educational Research Journal*, *20*, 309–331.

U.S. Department of Education, National Center for Education Statistics. (2009). Table 50: Children 3 to 21 years old served under Individuals with Disabilities Education Act, Part B, by type of disability: Selected years, 1976–77 through 2007–08. In U.S. Department of Education, National Center for Education Statistics (Ed.), *Digest of Education Statistics* (2009 ed.). Retrieved from http://nces.ed.gov/programs/digest/d09/tables/dt09_050.asp

U.S. Department of Education, National Center for Education Statistics. (2009). Table 51: Percentage distribution of students 6 to 21 years old served under Individuals with Disabilities Education Act, Part B, by educational environment and type of disability: Selected years, fall 1989 through fall 2007. In U.S. Department of Education, National Center for Education Statistics (Ed.), *Digest of Education Statistics* (2009 ed.). Retrieved from http://nces.ed.gov/programs/digest/d09/tables/dt09_051.asp

West, M. R., & Peterson, P. (2006). The efficacy of choice threats within school accountability systems: Results from legislatively induced experiments. *Economic Journal*, *116*, C46–C62.

Ysseldyke, J., Algozzine, B., & Epps, S. (1983). A logical and empirical analysis of current practice in classifying students as handicapped. *Exceptional Children*, *50*, 160–166.

Ysseldyke, J. E., Algozzine, B., Shinn, M. R., & McGue, M. (1982). Similarities and differences between low achievers and students classified learning disabled. *Journal of Special Education*, *16*, 73–85.

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