CHARTER SCHOOLS AND STUDENT ACHIEVEMENT IN FLORIDA

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Abstract
I utilize longitudinal data covering all public school students in Florida to study the performance of charter schools and their competitive impact on traditional public schools. Controlling for student-level fixed effects, I find achievement initially is lower in charters. However, by their fifth year of operation new charter schools reach a par with the average traditional public school in math and produce higher reading achievement scores than their traditional public school counterparts. Among charters, those targeting at-risk and special education students demonstrate lower student achievement, while charter schools managed by for-profit entities peform no differently on average than charters run by nonprofits. Controlling for preexisting traditional public school quality, competition from charter schools is associated with modest increases in math scores and unchanged reading scores in nearby traditional public schools.

1. INTRODUCTION

The efficacy of publicly funded school-choice programs has been fiercely debated in recent years. Proponents claim that school choice will not only provide a mechanism for students seeking to improve the quality of their own education but also engender competition that will lead to improvements in the quality of education for students who remain in traditional public schools. Those opposed to publicly funded school choice argue such programs will skim the best students, drain resources away from public schools, and promote racial/ethnic segregation.

While much attention has been paid to voucher programs in Milwaukee, Cleveland, and elsewhere, by far the more common vehicle for school choice is charter schools. Forty states and the District of Columbia have charter school laws in place, and approximately 698,000 students attended charters during the 2003–4 school year.[1] Like vouchers, charter schools represent a subsidized alternative to traditional public schools. Students are not charged any tuition, and charter schools rely on public funding for their operating budget. While the specifics vary across states, charter schools typically are not subject to many of the regulatory constraints governing traditional public schools; charters generally have considerable freedom in personnel and curriculum decisions.

In this article I utilize a new longitudinal database from Florida to address three key issues relating to charter schools and student achievement. First, how does the impact of charter schools on student achievement compare with traditional public schools? Second, to the extent that student performance varies among charter schools, what factors contribute to the difference in performance? Third, what competitive impact, if any, do charter schools have on traditional public schools?

To empirically analyze these issues I will focus on student achievement in traditional public schools and charters in Florida. Due to the size of its charter sector and the availability of data, Florida is an ideal laboratory for empirical analysis of charter schools. Charter schools have existed in Florida since the 1996–97 school year, when 5 schools began operation (see Table 1). The number of charter schools has rapidly grown to 258 in the 2003–4 school year. Florida now ranks third among the states in number of charters operating, and the 53,000 students enrolled in Florida charter schools in 2003–4 comprise 7.6 percent of the national total. Florida also possesses one of the most comprehensive systems in the nation for tracking student achievement; all public school students (whether in traditional or charter schools) must take annual standardized tests in each of grades 3–10.

1. National data on charter school laws and enrollment are from the Center for Education Reform (www.edreform.com).

Table 1 Charter Schools in Operation by Type, Changes in Operation, and Charter School Student Membership in Florida, 1996/1997–2002/2003

	CHARTER SCHOOLS OPERATING				CHANGES IN OPERATION		MEMBERSHIP	
School Year	**Total**	**Targeted**	**Conversion**	**Run by For-Profit**	**Openings**	**Closures**	**Number of Students**	**% of all Public School Students**
1996–97	5	2	0	0	5	0	400	0.02%
1997–98	31	10	1	1	26	2	3,500	0.15%
1998–99	78	26	3	4	49	3	10,000	0.43%
1999–00	113	40	3	9	38	2	17,200	0.72%
2000–1	148	50	4	15	37	11	27,200	1.12%
2001–2	190	58	7	32	53	1	39,900	1.60%
2002–3	232	65	11	48	43	8	50,700	2.06%

Note: The number of charters operating represents the number of charter schools in operation during any portion of the school year, including schools that closed during the school year. The count of charter schools is based on the assignment of school identification codes by the Florida Department of Education. Thus, a single charter school may have two branches in distinct geographic locations, or two charters serving distinct populations may physically reside in the same location. Charter Schools Opened includes all schools operating that did not exist at the end of the previous school year. Closures include all schools that ceased operating prior to the start of the next school year. Student totals are based on attendance during the October membership survey of public schools.

I begin by reviewing the extant empirical literature on charter schools in the next section. In the third section, I discuss methodological issues and present an empirical model of student achievement. This is followed by a description of the Florida data and the presentation of the empirical results. A final section summarizes the findings and their implications for policy.

2. PREVIOUS LITERATURE

Achievement in Charter Schools

Despite the size and importance of the charter school movement, quantitative analysis of the impact of charter schools on student achievement has been limited. Much of the existing research lacks sufficient controls for student characteristics which creates potential selection-bias problems due to the nonrandom assignment of students between charters and traditional public schools. However, a handful of recent papers account for the impact of student characteristics on achievement in charter schools by employing longitudinal data and estimating student-level, fixed-effects models.

Solmon, Paark, and Garcia (2001) analyze scores on the Stanford Achievement Test (SAT-9) for a panel of Arizona students in grades 3–11 over the 1998-2000 period.[2] Their three-year panel encompasses 40,000 total students, including 8,000 students who attended an Arizona charter school for at least one year. Their models incorporate fixed effects to control for time-invariant student characteristics but do not include lagged test scores to account for the cumulative effects of past educational inputs.[3] They find the first-year effect of attending a charter school on achievement is statistically insignificant for both reading and math. However, students who attend a charter school for two or three years experience achievement gains in both reading and math that exceed those of traditional public school students. Unfortunately, no measure of the age of charter schools is included in their analysis. Thus the measured student tenure effects may in part reflect differences in the maturity of charter schools, rather than the duration of charter school attendance.

Hanushek, Kain, and Rivkin (2002) analyze individual student achievement gains for four cohorts of Texas students in grades 4–7 during the

2. Solmon and Goldschmidt (2004) reanalyze the same data, limiting their analysis to reading scores. Employing a three-level hierarchial linear model, they find that students attending charter schools three straight years experience higher achievement growth than students enrolled only in traditional public schools. However, students who start in a charter school and switch to a traditional public school have significantly higher achievement growth than those who stay in charter schools. Further, the positive effects of charter attendance diminish with the grade level; achievement growth for charter-only students exceeds that of traditional-school-only students in elementary school, is equal by middle school, and is lower in high school.
3. The inclusion of lagged test scores to control for past educational inputs is discussed in more detail in the ethodology section below.

years 1996–2001. Their sample includes over 6,600 students who attended a charter school during the period and more than 800,000 students in total. Academic achievement is measured by year-to-year changes in standardized individual scores on the Texas Assessment of Academic Skills (TAAS), a criterion-referenced test. In addition to student-level fixed effects, their model includes controls for both charter school age and student mobility.

Hanushek, Kain, and Rivkin (2002) find that student achievement gains in both math and reading are lower in first-year charters than in the average traditional public school. These negative effects diminish rapidly, however, as the charters mature. For students in charters that have existed three years or more there are no statistically significant differences in reading or math achievement gains relative to peers attending traditional public schools. These average effects mask the wide variation in quality among both charters and traditional public schools. Hanushek, Kain, and Rivkin split their sample into geographic regions and include school-level fixed effects to measure differences in school quality. They find that higher-quality charter schools are often as good or better than traditional public schools, but the bottom quartile of charters are of much lower quality than the lowest quartile of traditional public schools in nearly all regions of Texas.

Booker et al. (2004a) also analyze achievement-score gains in Texas, though with a larger data set of six cohorts that spans 1995–2002 and covers 10,000 charter students and 1.4 million students in total.[4] In addition to controls for charter school age and student mobility, they also include school-level demographics to account for schoolwide peer effects. Similar to Hanushek, Kain, and Rivkin (2002), they find that new charter schools produce lower achievement gains in both math and reading than the average traditional public school and the relative performance of charters improves over time. However, while Hanushek, Kain, and Rivkin find that charters in operation three or more years are on par with the average traditional public school, Booker et al. (2004a) estimate that Texas charters in operation six years or more surpass the performance of traditional public schools. This effect must be viewed with caution, however, since it is based on the achievement gains of at most 256 students.[5]

4. Two of the study's authors previously conducted a study of Texas charter schools (Gronberg and Jansen 2001) which covered only three years and fewer than 1,000 charter students. This prior paper finds students in charter schools do not perform as well on the TAAS exam as do traditional public school students. However, students attending charters primarily serving at-risk students outperform students in traditional public schools with similar characteristics. These estimates may be biased, however, since Gronberg and Jansen include the lagged test score as an explanatory variable in their model but ignore the correlation between the lagged score and the error term and estimate the models using ordinary least squares.
5. Booker et al. (2004a) also estimate models that allow for different transition costs of moving from traditional public schools to charters vis-à-vis movement between traditional public schools. In this

Bifulco and Ladd (2004) analyze achievement data for students in North Carolina over the period 1996–2002. Their data set tracks five cohorts of students from grades 3–8. Their sample includes 496,000 students in total, 8,700 of which attended a charter school at least one year. Of the 8,700 students who attended a charter, about 5,700 are observed in both traditional and charter schools. They adopt the same methodology as Hanushek, Kain, and Rivkin (2002) but obtain some contrary results. Like Hanushek, Kain, and Rivkin, they find that students attending brand-new charters have lower test score gains in both reading and math than students in the average traditional public school. Similarly, they find that the negative charter effects tend to diminish as charters mature. However, unlike Hanushek, Kain, and Rivkin's results for Texas, Bifulco and Ladd find that in North Carolina the negative impact of charter schools on student achievement gains is statistically significant and quantitatively substantial even for schools in operation for five years.

The recent studies by Hanushek, Kain, and Rivkin (2002), Booker et al. (2004a), and Bifulco and Ladd (2004) are laudable for their application of fixed-effects modeling techniques to large panels of individual student data. However, their focus on the average effects of charter schools on student achievement does little to explain *why* charter schools perform better or worse than traditional public schools. Likewise, although Hanushek, Kain, and Rivkin document large quality variation among charter schools, neither they nor Bifulco and Ladd nor Booker et al. analyze characteristics of charter schools, other than age and student mobility, that determine charter school performance.

The Competitive Effects of Charter Schools

Advocates of charter schools claim that charters will not only provide a superior education to the students who enroll in them but will also foster competition that will lead to increases in the quality of traditional public schools. A number of authors, including Bettinger (1999), Eberts and Hollenbeck (2001), Greene and Forster (2002), and Holmes, DeSimone, and Rupp (2003), have attempted to test this claim by making cross-sectional school-level comparisons. Their results are generally quite mixed, ranging from large positive competitive effects in some instances to small or statistically insignificant competitive impacts in others. Hoxby (2003) also employs school-level data but compares traditional school performance before and after the introduction of charter school competition. Defining the competitive threshold as a districtwide 6 percent charter school enrollment share, she finds that in Arizona and Michigan charter

specification the negative first-year charter effect becomes insignificant. However, since most first-year charters are populated by students switching from traditional public schools to charters, the insignificant measured impact of first-year charter schools could simply be due to multicollinearity.

competition boosts traditional public school achievement score levels in both math and reading in fourth grade as well as increasing seventh-grade math scores.

Two recent studies, Holmes (2003) and Bifulco and Ladd (2004), exploit student-level data from North Carolina to estimate the impact of charter school competition on academic achievement in traditional public schools. Holmes uses cross-sectional student-level data over multiple years with controls for student race/ethnicity and gender. A student's prior school inputs are measured by a cubic form of the previous achievement score, while school-level fixed effects capture any time-invariant attributes of each school. He finds mixed results for more narrow market definitions; the existence of one or more charter schools within 6 miles is correlated with higher scores in math but not in reading, whereas the existence of a charter within 12 miles has the opposite effect—higher reading scores but unchanged math scores. When competition is measured at the county level, however, he finds the existence of a charter is associated with higher test scores for traditional public schools in both math and reading.

Bifulco and Ladd (2004) perform an analysis similar to Holmes (2003) but possess panel data on individual students and can thus fully account for both time-invariant student and school characteristics via fixed effects. In contrast to Holmes, Bifulco and Ladd find no significant effect of charter school competition on traditional public school performance. Neither the existence of one or more charters within 2.5 miles, 2.5 to 5 miles, or 5 to 10 miles has any statistically significant effect on test score gains of students in traditional public schools in North Carolina. Similarly, variation in the number of charter schools within 5 miles of a traditional public school does not have a significant effect on the average traditional public school's performance.

Booker et al. (2004b) also utilize panel data on individual students to investigate the impact of charter school competition on student performance within traditional public schools in Texas. Employing both student and school fixed effects, they find large and statistically significant positive effects of charter school competition. A 1 percent increase in the proportion of public school students attending charter schools within a district is associated with a 15 percent increase in annual math score gains and an 8 percent increase in annual reading score gains. Similarly, a 1 percent increase in the proportion of students leaving a school to move to a charter is associated with a 9 percent increase in math score gains and a 6 percent increase in reading score gains for those students who remain in the school. These competitive effects are even larger when instruments are used to account for possible endogeneity of charter school penetration. Interestingly, Booker et al. also find that the impact of charter school competition varies with the initial performance level of traditional public schools. Schools with the lowest proportion of students passing the statewide exam experience a large positive impact of charter competition, whereas schools initially in the highest quintile see a drop in test score gains with increases in charter penetration.

3. ECONOMETRIC MODEL

Following Todd and Wolpin (2003), consider a general cumulative model of student achievement:

$$A_{it} = A_t\left[\mathbf{F}_i(t), \mathbf{S}_i(t), \mu_{io}, \varepsilon_{it}\right]. \tag{1}$$

A_{it} is the achievement level for individual i at the end of their t-th year of life, $\mathbf{F}_{it}$ is a vector of family/parental inputs supplied during age t, $\mathbf{S}_{it}$ is a vector of school-supplied inputs during age t, μ_{io} is a composite variable representing individual time-invariant characteristics (e.g., innate ability), and ε_{it} captures any measurement error. $\mathbf{F}_i(t)$ and $\mathbf{S}_i(t)$ represent the entire input histories of family and school inputs, respectively.

If we assume that the cumulative achievement function, $A_t(\cdot)$, does not vary with age[6] and is additively separable, then we can rewrite the achievement level at age t as:

$$\begin{aligned} A_{it} = {} & \boldsymbol{\alpha}_1\mathbf{F}_{it} + \boldsymbol{\alpha}_2\mathbf{F}_{it-1} + \cdots + \boldsymbol{\alpha}_t\mathbf{F}_{i1} \\ & + \boldsymbol{\beta}_1\mathbf{S}_{it} + \boldsymbol{\beta}_2\mathbf{S}_{it-1} + \cdots + \boldsymbol{\beta}_t\mathbf{S}_{i1} + \gamma_t\mu_{io} + \varepsilon_{it} \end{aligned} \tag{2}$$

where $\boldsymbol{\alpha}_1$ and $\boldsymbol{\beta}_1$ represent the vectors of weights given to contemporaneous family and school inputs, $\boldsymbol{\alpha}_2$, and $\boldsymbol{\beta}_2$, the weights given to last year's inputs, and so on.

Estimation of equation (2) requires data on both current and all prior family and school inputs. However, administrative records contain only limited information on family characteristics and no direct measures of parental inputs. Therefore I assume that family inputs are constant over time and are captured by a student-specific fixed component, ϕ_i. The marginal effect of these fixed parental inputs on student achievement may vary over time and is represented by κ_t. This of course implies that the level of inputs selected by families does not vary with the level of school-provided inputs a child receives. For example, it is assumed that parents do not systematically compensate for

6. This assumption implies that the impact of an input on achievement varies with the time span between the application of the input and measurement of achievement but is invariant to the age at which the input was applied. Thus, for example, attending a private school in kindergarten has the same effect on achievement at the end of third grade as attending a private school in second grade has on fifth-grade achievement.

low-quality schooling inputs by providing tutors or other resources.[7] Given these assumptions, the achievement-level equation becomes:

$$\mathrm{A_{it}} = \boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{it}} + \boldsymbol{\beta}_2 \mathbf{S}_{\mathrm{it-1}} + \cdots + \boldsymbol{\beta}_{\mathrm{t}} \mathbf{S}_{\mathrm{i1}} + \kappa_{\mathrm{t}}\phi_{\mathrm{i}} + \gamma_{\mathrm{t}}\mu_{\mathrm{io}} + \varepsilon_{\mathrm{it}}. \tag{3}$$

The need for data covering the entire school input history can be avoided if one is willing to assume that the marginal impacts of all prior school inputs decline geometrically with the time between the application of the input and the measurement of achievement at the same rate (i.e., $\boldsymbol{\beta}_2 = \lambda\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_3 = \lambda^2\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_4 = \lambda^3\boldsymbol{\beta}_1$, and so on). The achievement equation can then be expressed as:

$$\mathrm{A_{it}} = \boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{it}} + \lambda\boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{it-1}} + \cdots + \lambda^{\mathrm{t-1}}\boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{i1}} + \kappa_{\mathrm{t}}\phi_{\mathrm{i}} + \gamma_{\mathrm{t}}\mu_{\mathrm{io}} + \varepsilon_{\mathrm{it}}. \tag{4}$$

Taking the difference between current achievement and λ times prior achievement yields:

$$\begin{aligned}\mathrm{A_{it}} - \lambda\mathrm{A_{it}} = &\left[\boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{it}} + \lambda\boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{it-1}} + \cdots + \lambda^{\mathrm{t-1}}\boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{i1}} + \kappa_{\mathrm{t}}\phi_{\mathrm{i}} + \gamma_{\mathrm{t}}\mu_{\mathrm{io}} + \varepsilon_{\mathrm{it}}\right] \\ &- \left[\lambda(\boldsymbol{\beta}_1 \mathbf{S}_{it-1}) + \lambda(\lambda\boldsymbol{\beta}_1 \mathbf{S}_{it-2}) + \cdots + \lambda(\lambda^{t-2}\boldsymbol{\beta}_1 \mathbf{S}_{i1}) \right. \\ &\left. + \lambda\kappa_{t-1}\phi_i + \lambda\gamma_{t-1}\mu_{io} + \lambda\varepsilon_{it-1}\right]. \end{aligned} \tag{5}$$

Collecting terms, simplifying, and adding $\lambda\mathrm{A_{it-1}}$ to both sides produces:

$$\mathrm{A_{it}} = \boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{it}} + \lambda\mathrm{A_{it-1}} + (\kappa_{\mathrm{t}} - \lambda\kappa_{\mathrm{t-1}})\phi_{\mathrm{i}} + (\gamma_{\mathrm{t}} - \lambda\gamma_{\mathrm{t-1}})\mu_{\mathrm{io}} + \varepsilon_{\mathrm{it}} - \lambda\varepsilon_{\mathrm{it-1}}. \tag{6}$$

Assuming the impact of parental inputs on achievement, κ_{t}, and the effect of the initial individual endowment on achievement, γ_{t}, change at constant rates, then $(\kappa_{\mathrm{t}} - \lambda\kappa_{\mathrm{t-1}})$ and $(\gamma_{\mathrm{t}} - \lambda\gamma_{\mathrm{t-1}})$ can be expressed as constants, κ and γ. Combining the family/parental inputs with the initial individual endowment into a single component yields:

$$\mathrm{A_{it}} = \boldsymbol{\beta}_1 \mathbf{S}_{\mathrm{it}} + \lambda\mathrm{A_{it-1}} + \nu_{\mathrm{i}} + \eta_{\mathrm{it}}. \tag{7}$$

where $\nu_{\mathrm{i}} = \kappa\phi_{\mathrm{i}} + \gamma\mu_{\mathrm{io}}$ and $\eta_{\mathrm{it}} = \varepsilon_{\mathrm{it}} - \lambda\varepsilon_{\mathrm{it-1}}$. In this so-called value-added specification, the current achievement level is a function of current school inputs, lagged achievement, and an individual-specific fixed effect.[8]

7. For evidence on the impact of school resources on parental inputs, see Houtenville and Conway (2003) and Bonesrønning (2004).
8. It is important to recognize that I am modeling achievement levels, not achievement growth. An achievement growth model would take the form $\Delta\mathrm{A_{it}} = \pi\mathbf{S}_{\mathrm{it}} + \lambda\Delta\mathrm{A_{it}} + \Psi_{\mathrm{i}} + \omega_{\mathrm{it}}$.

Education researchers typically estimate a restricted form of the value-added specification where the gain in student achievement from one year to the next (the "gain score") is a function of contemporaneous inputs and an individual-specific fixed effect (see, for example, Hanushek, Kain, and Rivkin 2002, Bifulco and Ladd 2004, and Booker et al. 2004a):

$$A_{it} - A_{it-1} = \Delta A_{it} = \boldsymbol{\beta}_1 \mathbf{S}_{it} + \nu_i + \eta_{it}. \tag{8}$$

This of course imposes the restriction that $\lambda = 1$ in equation (7).[9] As noted by Boardman and Murnane (1979) and Todd and Wolpin (2003), this implies that the effect of each input must be independent of when it is applied. In other words, school inputs each have an immediate one-time impact on achievement that does not decay over time. For example, the quality of a child's kindergarten must have the same impact on his achievement at the end of age five as it does on his achievement at age eighteen.[10]

In order to determine the impact of charter schools on educational achievement I utilize the value-added model, equation (7). Estimation of this model by ordinary least squares is problematic, however. The lagged achievement score regressor, A_{it-1}, will obviously be correlated with the lagged measurement error, ε_{it-1}, and thus ordinary-least-squares (OLS) estimates of equation (7) will be biased. In order to obtained unbiased parameter estimates I employ the dynamic panel data estimator developed by Arellano and Bond (1991). The Arellano and Bond model uses twice (and greater) lagged levels of the dependent variable as instruments for the lagged difference in the dependent variable in order to eliminate the correlation between the lagged dependent variable and the error term. The student-specific effect is eliminated by first-differencing the data. Asymptotic standard errors are utilized that are robust to general heteroskedasticity over individuals and over time.[11]

In order to provide a comparison to other studies, I will also estimate the restricted value-added model specified in equation (8). The obvious disadvantage of this model is the restriction on the decay rate of prior school inputs, 1. This model does have the advantage that it can be estimated by OLS, however, since there is no lagged dependent variable on the right side of the equation.

9. Alternatively, equation (8) can be interpreted as a special case of an achievement *growth* model, i.e., $\Delta A_{it} = \pi \mathbf{S}_{it} + \lambda \Delta A_{it} + \Psi_i + \omega_{it}$, where λ equals zero (achievement growth is independent of past school inputs).

10. Krueger (1999) makes a similar point and provides empirical evidence that class size reduction has the greatest impact on achievement the first year a student is in a small class.

11. Standard error estimates adjusted for clustering of errors are not available for the Arellano and Bond model.

Robust standard errors are provided, which allow for clustering of errors at the school level.

Variation in school inputs, $\mathbf{S}_{it}$, will be measured by student mobility (changing schools between academic years and within academic years), the general category of school attended (traditional public or charter) and the type of charter attended (e.g., whether or not it targets a specific student population, whether it is run by a nonprofit organization or a for-profit management firm, and whether it is a conversion from a traditional public school or a school that began *de novo*). Thus, any estimated differences between charter and traditional public schools will represent the combined effects of differences in all other school inputs (teacher quality, class size, curriculum, etc.).

4. DATA AND RESULTS

Data

The Florida Department of Education's Education Data Warehouse maintains longitudinal records on all Florida public school students, from preschool through college, beginning with the 1995/1996 school year. The Data Warehouse includes not only test scores and student demographic data but also information on enrollment, attendance, disciplinary actions, and participation in exceptional student education and limited English proficiency programs.

Although student records are available since the 1995–96 school year, statewide standardized testing did not begin in Florida until school year 1997–98. In that year students began taking the "Sunshine State Standards" Florida Comprehensive Achievement Test (FCAT-SSS). This is a criterion-based exam designed to test for the skills that students must achieve at each grade level in order to be promoted and to eventually graduate from high school. The FCAT-SSS was administered in selected grades from 1997–98 through 1999–2000 and has been administered in grades 3–10 since the 2000–1 school year. Beginning with the 1999–2000 school year a second test, the FCAT Norm-Referenced Test (FCAT-NRT), has been administered to all third through tenth graders. The FCAT-NRT is a version of the SAT-9 achievement test used throughout the country. The FCAT-NRT scores are scaled so that a one-point increase in the score at one place on the scale represents the same difference in performance as a one-point increase anywhere else on the scale.[12] The Stanford-9 is a vertically scaled exam, thus scale scores typically increase with

12. See Harcourt Brace Educational Measurement (1997, p. 17). The use of scale scores to evaluate student achievement is important, since a one-unit change has the same meaning for low- and high-achieving students. Other types of measures, such as standard deviations from the mean score, are potentially problematic; it is not clear that a 0.1 standard deviation increase in a test score, starting one standard deviation from the mean, is the same as a 0.1 standard deviation increase for someone with an initial score equal to the sample mean.

Table 2 Characteristics of Students Enrolled in Grades Pre-K–12 by School Type, 2002–3 School Year

	Traditional Public Schools	Charter Schools
Number of students	2,588,172	52,860
Percent black	24.43	28.62
Percent Hispanic	20.70	21.07
Percent female	48.38	49.94
Percent free/reduced-price lunch	44.61	36.54
Percent with limited English proficiency	10.73	8.76
Percent in special education (excluding gifted)	14.47	12.36
Percent gifted	4.23	2.67

Note: Student totals are based on enrollment throughout the school year. School type is determined by the longest duration of enrollment. Program participation is based on the October membership survey of public schools.

the grade level. I use FCAT-NRT scale scores in all of the subsequent analyses. In addition to providing four continuous years of data, use of the FCAT-NRT minimizes potential biases associated with “teaching to the test” since all school accountability standards and promotion and graduation criteria in Florida are based on the FCAT-SSS rather than the FCAT-NRT.

Characteristics of Students in Charter Schools

Table 2 provides a breakdown of student characteristics for both traditional and chartered public schools. The characteristics of students attending charter schools in Florida are quite similar to those of students in traditional public schools. Except for a somewhat lower proportion of students from low-income households (as indicated by free/reduced-price lunch receipt) and gifted students and a somewhat higher enrollment of black students, there is little difference in the measured characteristics of students attending charters versus traditional public schools in Florida. Thus, at least at an aggregate level there appears to be no strong evidence that charter schools cream the best students from traditional public schools.

Student Achievement in Charter Schools

Estimation of the value-added and restricted-value-added models with individual fixed effects requires a minimum of three consecutive years of achievement score data. Thus, my analysis focuses on the sample of Florida public school students in grades 3–10 who took the FCAT-NRT three consecutive years

Table 3 Enrollment Patterns of Students in Sample (Florida Students Who Took the FCAT-NRT in Three Consecutive Years, 1999–2000 through 2002–3)

Enrollment Pattern	Number of Students	Percent
All Students	**1,090,242**	**100.00%**
Students with All Enrollments Known	**1,079,028**	**98.97%**
Students with No Observed Transitions	**1,053,765**	**96.65%**
Only Tradtional	1,050,131	96.32%
Only Charter	3,634	0.33%
Students with One or More Observed Transitions	**25,263**	**2.32%**
One Transition	20,746	1.90%
Traditional to Charter	15,446	1.42%
Charter to Traditional	5,300	0.49%
Two Transitions	4,430	0.41%
Traditional to Charter to Traditional	4,288	0.39%
Charter to Traditional to Charter	142	0.01%
Three Transitions	87	0.01%
Traditional to Charter to Traditional to Charter	67	0.01%
Charter to Traditional to Charter to Traditional	20	0.00%
Students with One or More Unknown Enrollments	**11,214**	**1.03%**

during the period 1999–2000 through 2002–3.[13] This initial sample includes over 1 million students, more than 28,000 of which attended a charter school in one or more of the three sample school years. Since the parameters in fixed-effects models are identified by within-student intertemporal variation, transitions between charters and traditional public schools are key to the analysis. Table 3 provides a breakdown of the enrollment patterns of students and indicates that over 25,000 students in the sample switched at least once between traditional public schools and charters—substantially more than in any previous study of charter school performance.

A potential source of bias in both the value-added and restricted-value-added achievement models is that the choice of moving to a charter school may be due to a temporary drop in student performance. For example, a student could draw a relatively low-quality teacher one year and perform poorly relative to past years, which could in turn lead the child's parents to switch the student from a traditional public school to a charter school. If the student's performance would have rebounded in the next year (even if they had stayed in a traditional public school), then the measured effect of charter schools will

13. The sample includes students who repeat a grade as well as those making a normal one-grade progression from year to year. Separate grade-level dummies are included in the models for grade repeaters.

be biased upward. To investigate the possibility of such mean-reversion bias, I estimate a probit model of the determinants of switching from a traditional public school to a charter school.

Computing the deviation in prior-year performance from the past trend requires four years of data (two years to establish the previous trend, one year prior to the enrollment decision and a fourth year covering the choice between traditional public schools and charter schools). Thus my sample is the group of students in 2002–3 who attended traditional public schools and took the FCAT-NRT in each of the prior years 1999–2000 through 2001–2. Controls for student demographics as well as the number of available charter schools within a 5-mile radius are included in the model. The results, presented in Table 4, indicate that there is no significant correlation between last year's deviation from the prior achievement trend and the current year's decision to enroll in a charter school.[14] Indeed, the mean-reversion hypothesis would predict a negative correlation between prior-year deviation from trend and current-year charter enrollment, yet the point estimates are all positive. Thus estimates of the value-added and restricted-value-added models should not be subject to bias resulting from reversion to the mean.

Table 5 presents estimates of the average effect of charter schools on student achievement in both math and reading. The value-added results indicate that student achievement in the average charter school is 1.2 scale-score points lower in math and 0.5 points lower in reading than the average traditional public school. The size of these differentials depends on the basis for comparison. In terms of cross-sectional differences among students, the differentials are not very large. The estimated scale-score differential in math is equivalent to 2 percent of the standard deviation in all math scores, which equals 49. Likewise, the scale-score differential in reading is only 1 percent of the standard deviation in all reading scores of 47. However, if one compares the average-charter achievement differentials to the average year-to-year score gains, the differences are more substantial, equivalent to 8 percent of the average 16-point year-to-year gain in math and 4 percent of the average 12-point year-to-year gain in reading.

The effects of student mobility on achievement are captured by three variables: *Number of Schools, Structural Move*, and *Nonstructural Move*. The first variable, *Number of Schools*, measures the number of schools a student attended during the current school year, thereby controlling for within-year

14. My measure of deviation from prior achievement is the difference in achievement gains, $\Delta A_{t-1} - \Delta A_{t-2}$. This is equivalent to the difference in the achievement level, A_{t-1}, and the expected achievement level based on a linear extrapolation of past performance, A^*_{t-1}. The predicted level would be $A_{t-2} + (A_{t-2} - A_{t-3})$ which equals $A_{t-2} + \Delta A_{t-2}$. The difference between the actual achievement level and the predicted level in $t-1$ is $(A_{t-1} - (A_{t-2} + \Delta A_{t-2})$ or $\Delta A_{t-1} - \Delta A_{t-2}$.

Table 4 Probability of Switching from a Traditional Public School to a Charter School, 2002–3 (Florida Students Who Were Enrolled in Traditional Public Schools and Took the FCAT-NRT in Each of the Years 1999–2000 through 2001–2)

Math Achievement Gain$_{t-1}$– Math Achievement Gain$_{t-2}$	2.3×10^{-6} (1.42)		2.5×10^{-6} (1.60)
Reading Achievement Gain$_{t-1}$– Reading Achievement Gain$_{t-2}$		3.2×10^{-7} (0.21)	2.3×10^{-8} (0.02)
Number of Charter Schools within 5 Miles$_t$	$1.0 \times 10^{-3**}$ (11.35)	$1.0 \times 10^{-3**}$ (11.36)	$1.0 \times 10^{-3**}$ (11.13)
Free/Reduced-Price Lunch$_{t-1}$	1.7×10^{-4} (0.60)	1.9×10^{-4} (0.67)	1.8×10^{-4} (0.64)
Limited English Proficiency$_{t-1}$	-1.3×10^{-4} (0.23)	-2.8×10^{-4} (0.53)	-1.9×10^{-4} (0.35)
Special Education$_{t-1}$	1.4×10^{-4} (0.67)	1.6×10^{-4} (0.78)	1.6×10^{-4} (0.77)
Gifted$_{t-1}$	$-9.0 \times 10^{-4*}$ (2.18)	$-0.87 \times 10^{-4*}$ (2.16)	$-9.0 \times 10^{-4*}$ (2.17)
Black	$1.5 \times 10^{-3**}$ (5.32)	$1.5 \times 10^{-3**}$ (5.48)	$1.5 \times 10^{-3**}$ (5.30)
Hispanic	$9.3 \times 10^{-4*}$ (2.48)	$9.5 \times 10^{-4**}$ (2.64)	$9.3 \times 10^{-4*}$ (2.50)
Multiracial	2.4×10^{-4} (0.35)	3.6×10^{-4} (0.56)	2.8×10^{-4} (0.42)
Female	$-1.1 \times 10^{-4**}$ (0.83)	-1.1×10^{-4} (0.87)	-1.3×10^{-4} (0.99)
Observed probability of attending a charter school	3.34×10^{-3}	3.29×10^{-3}	3.33×10^{-3}
Number of students	614,271	630,158	608,357
Number of observations	614,271	630,158	608,357

Notes: Absolute values of robust t-ratios adjusted for clustering of errors at the prior-school level in parentheses. All models include grade dummies and a constant. Reported coefficients are marginal effects. For charter school students the number of charter schools within a five-mile radius is based on the location of the traditional public school that a plurality of their prior-year traditional public school classmates attend in the current year.

* statistical significance at .05 level, ** significance at the .01 level in a two-tailed test.

mobility.[15] The second and third variables identify two kinds of between-year school transitions. Following Hanushek, Kain, and Rivkin (2002), structural moves are defined as situations where a student moves from one school to another and at least 30 percent of his fellow students in the same grade at the initial school move to the same school. Thus the variable *Structural Move* captures the effects of normal transitions from elementary to middle and middle

15. Only schools attended two weeks or more are counted. For example, a student who normally attends a single school but is temporarily assigned to a juvenile-justice school for a short duration and then returns to his regular school is counted as attending one school.

Table 5 Estimates of the Average Effect of Charter Schools on Student Achievement

	MATH		READING	
	Value-Added Model	**Restricted Value-Added Model**	**Value-Added Model**	**Restricted Value-Added Model**
Charter$_t$	–1.202** (6.47)	–0.932* (2.56)	–0.474* (2.32)	–0.022 (0.06)
Number of Schools$_t$	–0.742** (9.64)	–0.638** (4.88)	–0.638** (7.26)	–0.666** (5.06)
Structural Move$_t$	–0.967** (17.03)	–1.933** (8.01)	–1.128** (17.81)	–1.806** (9.88)
Nonstructural Move$_t$	–0.633** (12.37)	–0.870** (5.57)	–0.555** (9.72)	–0.680** (5.30)
Achievement Score$_{t-1}$	0.088** (36.58)		0.203** (104.67)	
Number of students	1,065,443	1,065,443	1,068,161	1,068,161
Number of observations	1,704,593	2,768,486	1,724,663	2,791,246

Notes: Absolute values of robust t-ratios appear in parentheses. For the restricted-value-added model, the reported t-ratios account for clustering of errors at the school level. All models include time and grade dummies and a constant as appropriate. Reported number of observations for the value-added model is number of observations after first-differencing of variables.

* statistical significance at .05 level, ** significance at the .01 level in a two-tailed test.

to high school as well as the impact of significant school rezonings. Correspondingly, the *Nonstructural Move* variable represents students who attend a school different from the one attended at the end of the preceding school year but are not joined by at least 30 percent of their former schoolmates. This encompasses family relocations as well as movements between schools to attend magnet or other specialized programs. Consistent with the findings of other researchers, all of the mobility measures have significant negative effects on student achievement; and structural moves are more harmful to student learning than nonstructural moves.

It is also interesting to note that the maintained assumption of the restricted-value-added model, that the effect of past school inputs doesn't decay (i.e., $\lambda = 1$), is not supported by the data.[16] Estimates from the unrestricted value-added model indicate a value for λ of 0.09 in math and 0.20 in reading.[17] These estimates suggest that the effects of prior schooling inputs on

16. I also directly estimated the cumulative function specified in equation (3). The effects of lagged charter school attendance and lagged intrayear and between-year school changes also suggest a value of lambda less than one.
17. The first-stage estimation of the lagged dependent variable in the value-added model yielded R^2 values of 0.12 for math and 0.24 for reading using twice-lagged achievement levels as an instrument and R^2 values of 0.23 for math and 0.35 for reading when both twice-lagged and three-times-lagged

the current achievement (holding student ability constant) diminish rapidly, decaying 80–90 percent after one year and 96–99 percent after two.

The results presented in Table 5 mask the important effects of maturation on charter school performance. As previous studies have demonstrated, one would expect that performance improves as charter schools age and become better established. The important issue is how charter schools compare to traditional public schools in the long run. To address this question I estimate two models: one with a linear age trend in charter school performance and another with separate effects for first-year, second-year, third-year, and fourth-year charters and traditional public schools.[18] In the linear-trend model charter age is defined as the number of prior school years the school has been in operation, so the age of charters in their first school year of operation is zero. Estimates of these two models are presented in the upper and lower panels, respectively, of Table 6.

Estimates of both models (Table 6) indicate that student achievement in math and in reading are lower, on average, in brand-new charter schools than in traditional public schools. Value-added model estimates indicate math test scores are 2.0 to 2.1 points (13 percent of average annual gain) lower in first-year charters, while point estimates from the restricted-valued-added models yield somewhat higher differentials of 2.5 to 2.7 points. For reading scores the value-added linear-trend model indicates a deficit of 1.5 scale points (12 percent of average annual gain) for new charters, while the model with an unconstrained age profile yields an estimated difference of 1.2 points (10 percent of average annual gain). For the restricted-value-added models there are no statistically significant differences in reading achievement between first-year charters and mature traditional public schools.

The results presented in Table 6 also show that both math and reading scores in charter schools generally improve as the school matures. The value-added model estimates indicate that charters operating five years or more are on par with the average mature traditional public school in math achievement and produce reading achievement scores that are 1.1 scale-score points (9 percent of average annual achievement gain) higher than their traditional public

achievement levels are included as instruments. I also estimated value-added models with twice-lagged levels of student attendance, retention, and disciplinary incidents as additional instruments. The results differed little from those presented in Table 5, and a Sargan test rejected the validity of the additional instruments. Similarly, the R^2 values of the first-stage regression changed little with the additional instruments; they were 0.13/0.24 for math and 0.24/0.36 for reading. In all cases F-tests reject the null hypothesis that the coefficients on the instruments are zero at better than a 99.99 percent confidence level.

18. I make no distinction between charters operating five years and those operating six or more years since there are fewer than thirty schools that began operation prior to 1998–99 and that were still in operation during the last year of the sample, 2002–3.

Table 6 Estimates of the Effect of Charter Schools on Student Achievement, Controlling for School Age

	MATH		READING	
	Value-Added Model	**Restricted Value-Added Model**	**Value-Added Model**	**Restricted Value-Added Model**
Charter	–2.139** (7.28)	–2.730** (3.21)	–1.504** (4.60)	–1.256 (1.78)
Charter % Age of Charter	0.441** (4.28)	0.810** (2.62)	0.482** (4.20)	0.552* (2.29)
First-Year Charters	–2.002** (5.69)	–2.510* (2.26)	–1.197** (3.05)	–1.361 (1.44)
Second-Year Charters	–1.118** (3.65)	–0.585 (0.80)	–0.930** (2.74)	–0.140 (0.20)
Third-Year Charters	–2.270** (7.92)	–2.876** (2.92)	–1.087** (3.39)	–0.596 (0.83)
Fourth-Year Charters	–1.035** (3.85)	–0.894 (1.33)	–0.424 (1.41)	0.173 (0.23)
Fifth-Year and Older Charters	0.258 (0.82)	1.655* (2.00)	1.103** (3.13)	1.511* (2.37)
First-Year Traditional Public Schools	–0.577* (2.14)	–0.287 (0.25)	–0.189 (0.63)	1.090 (0.96)
Second-Year Traditional Public Schools	–0.720** (5.50)	–0.122 (0.24)	–0.038 (0.26)	0.734 (1.75)
Third-Year Traditional Public Schools	0.093 (0.80)	0.604 (1.49)	0.106 (0.81)	0.596 (1.83)
Fourth-Year Traditional Public Schools	0.413 (3.54)	0.648 (1.38)	0.001 (0.00)	0.175 (0.40)
Number of students	1,065,443	1,065,443	1,068,161	1,068,161
Number of observations	1,704,593	2,768,486	1,724,663	2,791,246

Notes: Absolute values of robust t-ratios appear in parentheses. For the restricted-value-added model, the reported t-ratios account for clustering of errors at the school level. All models include time and grade dummies and a constant as appropriate. Models also include control variables reported in Table 5. Reported number of observations for the value-added model is the number of observations after first-differencing of variables.

* statistical significance at .05 level, ** significance at the .01 level in a two-tailed test.

school counterparts. The restricted-value-added model estimates suggest even greater improvement in charter performance over time; fifth-year and older charters yield math and reading scores that are 1.7 and 1.5 scale-score points, respectively, above the average mature traditional public school. In contrast to charter schools, traditional public schools do not demonstrate any consistent pattern of maturation effects.[19]

The results presented in Table 6 may not provide an accurate picture of charter school maturation effects because they do not control for the age

19. The difference in maturation patterns between traditional public schools and charters is not surprising. Traditional public schools almost always start out with newly constructed facilities, an established curriculum, and can draw on administrators and faculty from established public schools. In contrast, charters often begin in temporary quarters designed for other purposes, must recruit faculty from a variety of sources and frequently are attempting to implement a new curriculum.

of schools at the time they become charters. The vast majority of charter schools in Florida are created *de novo*. However, as indicated in Table 1, there are a growing number of "conversion charters"—traditional public schools that choose to become charter schools.[20] Since these conversion charters have been in operation for many years, one would expect that the number of years since becoming a charter school would not significantly affect their performance. Table 7 presents two sets of estimates that constrain the effect of age since acquiring charter status to be zero for conversion charters.[21] In the top panel, nonconversion charter performance varies with age in a linear fashion, while in the bottom panel, separate intercepts are included for first-year, second-year, third-year, and fourth-year nonconversion charters.[22]

When the distinction between conversion and nonconversion charters is made, a clear maturation pattern for nonconversion charters emerges. Estimates from the value-added model indicate new nonconversion charters produce achievement test scores 2.2 to 2.4 points (14 to 15 percent of annual achievement gain) lower in math and 2.2 to 2.4 points (18 to 20 percent of annual achievement gain) lower in reading. These deficits diminish over time, however. In math the gap closes by about a half-point per year, and there is no statistically significant difference in math achievement scores for fourth-year and older nonconversion charters and the average traditional public school. For reading, the improvement in achievement scores with charter age is even more rapid. Reading test scores are estimated to rise an average of 0.72 points with each year of charter operation. Charters operating for five years or more show reading achievement levels that exceed the average traditional public school by 1.3 scale-score points (10 percent of average annual achievement gain). Estimates from the restricted-value-added model show similar patterns: both the intial charter deficit and subsequent improvement from maturation are greater.

In addition to their age, charter schools vary in numerous dimensions, including curricular emphasis, the student population they serve, and their

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20. In Florida, conversion requires separate affirmative majority votes by both the parents and faculty of a school and subsequent approval by the local school board.
21. I also estimated models that allowed for a nonzero maturation effect for conversion charters that differed from that for nonconversion charters. The maturation effect for conversion charters was negative and significant in the value-added model for math and insignificantly different from zero in all other specifications. The other results were nearly identical to the estimates presented in Table 7. Given the small number of older conversion charters, the negative estimated maturation effect for math scores could represent some unmeasured attributes of the particular schools that were early converters.
22. Conversion charters are placed in the same category as nonconversion charters in their fifth or higher year of operation.

Table 7 Estimates of the Effects of Charter Schools on Student Achievement, Controlling for Charter School Age and Charter School Type

	MATH		READING	
	Value-Added Model	**Restricted Value-Added Model**	**Value-Added Model**	**Restricted Value-Added Model**
Charter	–2.215** (4.63)	–3.401** (2.67)	–2.448** (4.59)	–2.295* (2.32)
Nonconversion Charter × Age of Charter	0.543** (3.98)	1.097** (2.65)	0.715** (4.74)	0.788* (2.50)
Conversion Charter	2.213** (2.72)	2.444 (1.22)	1.233 (1.39)	1.001 (0.74)
Targeted Charter	–1.192* (2.21)	–0.292 (0.25)	–0.410 (0.70)	0.084 (0.09)
Charter Managed by For-Profit Firm	–0.314 (0.59)	–0.781 (0.84)	0.156 (0.27)	0.083 (0.08)
First-Year Nonconversion Charters	–2.414** (3.94)	–4.204* (2.51)	–2.222** (3.30)	–3.306** (2.81)
Second-Year Nonconversion Charters	–1.079* (2.30)	0.022 (0.02)	–1.474** (2.84)	–0.380 (0.43)
Third-Year Nonconversion Charters	–1.673** (4.36)	–2.323 (1.89)	–0.836 (1.95)	–0.515 (0.59)
Fourth-Year Nonconversion Charters	–0.635 (1.83)	–0.456 (0.57)	–1.034** (2.63)	–0.858 (1.23)
Fifth-Year and Older Charters	0.360 (0.92)	1.997* (2.10)	1.276** (2.94)	1.840** (2.80)
Conversion Charter	–0.375 (0.49)	–2.932 (1.63)	–2.487** (2.98)	–3.089** (2.73)
Targeted Charter	–1.239* (2.29)	–0.477 (0.40)	–0.499 (0.85)	–0.053 (0.05)
For-Profit Charter	–0.315 (0.59)	–1.102 (1.06)	0.071 (0.12)	0.035 (0.04)
Number of students	1,061,668	1,061,668	1,064,390	1,064,390
Number of observations	1,696,732	2,756,859	1,716,612	2,779,432

Notes: Absolute values of robust t-ratios appear in parentheses. For the restricted-value-added model, the reported t-ratios account for clustering of errors at the school level. Models in the lower panel include dummy variables representing traditional public schools in their first, second, third, and fourth year of operation. All models include time and grade dummies and a constant as appropriate. All models also include control variables reported in Table 5. Reported number of observations for the value-added model is the number of observations after first-differencing of variables.

* statistical significance at .05 level, ** significance at the .01 level in a two-tailed test.

organization. The models presented in Table 7 control for two important attributes of charter schools besides age: whether they target a particular student population and whether they are operated by a for-profit management company.

Greene, Forster, and Winters (2003) argue that most comparisons of charter and traditional public schools are biased because a large proportion of charter schools are targeted to serve educationally disadvantaged populations, such as students with disabilities, students at risk of dropping out, and low-income and migrant students.[23] Given that I control for student characteristics with individual-specific fixed effects, this should not be an issue. However, if specialized charters place a greater weight on factors that are not measured by achievement tests (e.g., life-management skills, vocational skills, foreign languages, performing arts), then they may have lower test scores than schools with a more traditional emphasis on core academic skills. To account for this, the models presented in Table 7 contain a dummy variable indicating charters that identify themselves as serving a targeted population.[24] In the value-added models, targeted charters are estimated to have math test scores that are 1.2 scale-score points lower than the scores for charter schools serving a general population. There are no statistically significant differences in reading test scores between targeted and nontargeted charters.

The other dimension of charter schools I measure is their organization. In Florida, as elsewhere, the majority of charter schools are run by local nonprofit entities. However, a growing number of charter schools are being managed by for-profit firms. If managers of for-profit educational firms are residual claimants on the net income of schools, they have a clear incentive to operate schools efficiently. Since operating revenues in charter schools are essentially constrained to equal the funding level of traditional public schools, for-profit management companies will have an incentive to minimize the cost of providing a given level of educational services. In contrast, operators of not-for-profit schools will seek to maximize their utility, which typically would include the welfare of students but might encompass other objectives as well.[25] Thus from a theoretical standpoint it is not clear which type of firm would produce the greatest contribution to student achievement.

The estimates presented in Table 7 do not show any difference in performance between nonprofit charter schools and charters run by for-profit management companies. In both the value-added and restricted-value-added

23. Greene, Forster, and Winters (2003) find that when the school-level achievement gains of nontargeted charters are compared to those of traditional public schools, charters outperform the average traditional public school. However, their models do not account for the age of charters and exclude conversion charters. Since most nonconversion charters are young, the relatively high year-to-year achievement gains may be due to charter maturation rather than an indicator of superior performance relative to traditional public schools.
24. The information on targeting by Florida charter schools is based on survey data from Greene, Forster, and Winters (2003), a separate survey of Florida charters conducted by Robert Crew, and information from school Web sites.
25. For a more detailed discussion of the incentives in nonprofit versus for-profit firms see Lien (2002) and references cited therein.

models the differences in math and reading achievement test scores between the two types of organizational forms are statistically insignificant.

In order to measure the effectiveness of charter schools at different grade levels, I reestimate the value-added and restricted value-added models for three grade groupings: elementary (grades 4–5), middle (grades 6–8), and high school (grades 9–10).[26] The results are presented in Table 8. For reading, the negative effect of first-year charters is greatest in the earlier grades, but the maturation effect is greater as well. For elementary students, the value-added model estimates indicate that first-year charters are associated with a 4.1-point decline in achievement test scores, but this deficit is eliminated by the fourth year of operation. For middle school students, the first-year-charter deficit is smaller (2.6 scale-score points), and the annual improvement is smaller as well (0.6 points). At the high school level, there is no statistically significant difference between reading scores for new charters and the average traditional public high schools. For math, the pattern is reversed; the differences between new charters and traditional public schools are greatest at the high school level. Students attending a brand-new charter high school experience a 3.5-point deficit in math achievement scores, but after three years of operation the math achievement score deficit is eliminated. For middle schools the initial deficit for new charters is only 2.1 scale-score points, but the improvement associated with charter maturation is also smaller; middle school charters reach a par with traditional public schools in math after five years of operation. At the elementary school level, new charters are on par with traditional elementary schools, and there is no significant improvement in their scores relative to traditional public schools as the charters mature. Interestingly, these different patterns for reading and math achievement also show up in the measured effects of conversion charters. The effect of conversion charters is significant only at the high school level for math and at the elementary school level for reading.

The models presented in Tables 7 and 8 do not differentiate between charters targeting different populations of students. In 2002–3, approximately 22 percent of charter students in my sample attend a school that identified themselves as targeting a specific student population. Among students attending such targeted charters, over half attend a school that is designed to serve at-risk students. The second most frequent category of targeted charters are those with programs directed toward serving students with disabilities; 17 percent of students attending targeted charters go to schools that emphasize

26. Given that achievement tests are administered in grades 3–10 and three annual scores are required to estimate the model, the elementary school group includes fifth-grade students plus fourth graders who repeated either grade 3 or grade 4.

Table 8 Value-Added Estimates of the Effects of Charter Schools on Student Achievement by Grade Level

	MATH			READING		
	Elementary (Grades 4–5)	**Middle (Grades 6–8)**	**High School (Grades 9–10)**	**Elementary (Grades 4–5)**	**Middle (Grades 6–8)**	**High School (Grades 9–10)**
Value-Added Model						
$Charter_t$	–1.459 (1.12)	–2.098** (3.44)	–3.473** (3.81)	–4.080** (2.85)	–2.613** (3.73)	–0.550 (0.53)
Nonconversion $Charter_t$ × Age of $Charter_t$	–0.196 (0.53)	0.416* (2.50)	1.523** (5.13)	1.302** (3.33)	0.580** (3.03)	0.661* (2.01)
Conversion $Charter_t$	3.832 (1.60)	0.406 (0.38)	6.208** (4.38)	5.993* (2.33)	0.620 (0.54)	0.239 (0.14)
Targeted $Charter_t$	–6.398** (3.65)	–0.509 (0.70)	–1.979* (2.26)	–5.697** (3.14)	1.225 (1.50)	–1.756 (1.78)
For-Profit $Charter_t$	–2.774 (1.79)	0.439 (0.68)	0.057 (0.05)	0.034 (0.02)	0.329 (0.46)	–0.207 (0.18)
Number of students	302,885	615,699	397,188	303,901	617,715	398,387
Number of observations	310,627	874,490	511,615	311,734	891,467	513,411
Restricted-Value-Added Model						
$Charter_t$	–2.641 (0.86)	–2.139 (0.77)	–2.384 (0.40)	–3.216 (1.10)	–2.941 (1.30)	–4.950 (1.51)
Nonconversion $Charter_t$ × Age of $Charter_t$	0.420 (0.43)	0.983 (0.99)	1.035 (0.33)	2.018* (2.03)	0.801 (1.15)	2.087 (1.55)
Conversion $Charter_t$	7.158 (0.65)	–2.953 (0.91)	7.610 (0.91)	3.983 (0.60)	–0.825 (0.27)	–1.767 (0.39)
Targeted $Charter_t$	–7.709* (2.04)	1.484 (0.77)	–5.378 (0.86)	–9.765** (3.53)	2.683 (1.48)	–2.183 (0.67)
For-Profit $Charter_t$	–2.301 (0.79)	–1.167 (0.54)	3.486 (0.76)	–3.299 (1.03)	–1.772 (0.92)	4.939 (1.51)
Number of students	302,885	615,699	397,188	303,901	617,715	398,387
Number of observations	613,521	1,210,689	646,119	615,664	1,213,506	648,230

Notes: Absolute values of robust t-ratios appear in parentheses. For the restricted-value-added model, the reported t-ratios account for clustering of errors at the school level. All models include time and grade dummies and a constant as appropriate. All models also include control variables reported in Table 5. Reported number of observations for the value-added model is the number of observations after first differencing of variables. Since testing begins in grade 3, the grade 4 sample includes only those students who repeated grade 3 or grade 4 and thus have 3 annual test scores.

* statistical significance at .05 level, ** significance at the .01 level in a two-tailed test.

special education. Approximately 25 percent of students attending targeted charters are at schools with other specializations. Some schools emphasize performing arts, multicultural education, or primarily serve migrants or gifted students.

Table 9 Value-Added Estimates of the Effects of Charter Schools on Student Achievement, Controlling for Charter School Age, Charter School Type, and Target Population

	MATH		READING	
	Value-Added Model	**Restricted Value-Added Model**	**Value-Added Model**	**Restricted Value-Added Model**
$Charter_t$	–3.206** (6.42)	–4.716** (3.29)	–2.890** (5.19)	–2.656* (2.43)
Nonconversion $Charter_t$ × Age of $Charter_t$	0.905** (6.28)	1.568** (3.28)	0.882** (5.52)	0.926** (2.61)
Conversion Charter	3.280** (3.93)	3.890 (1.81)	1.685 (1.86)	1.384 (0.95)
Charter Targeting At-Risk Students	–2.036** (2.86)	–2.120 (1.44)	–0.855 (1.06)	–0.581 (0.41)
Charter Targeting Special-Ed. Students	–8.042** (6.12)	–7.459** (3.75)	–2.409 (1.73)	–0.589 (0.23)
Charter Targeting Other Students	3.829** (3.95)	5.480** (2.89)	2.033 (1.90)	1.739 (1.08)
For-Profit Charter	0.070 (0.13)	–0.257 (0.28)	0.301 (0.51)	0.128 (0.12)
Number of students	1,061,542	1,061,542	1,064,259	1,064,259
Number of observations	1,696,426	2,756,428	1,716,290	2,778,981

Notes: Absolute values of robust t-ratios appear in parentheses. For the restricted-value-added model, the reported t-ratios account for clustering of errors at the school level. All models include time and grade dummies and a constant as appropriate. Models also include control variables reported in Table 5. Reported number of observations for the value-added model is the number of observations after first-differencing of variables.

* statistical significance at .05 level, ** significance at the .01 level in a two-tailed test.

Estimates of a model that allows the impact of charter schools on student achievement to vary with the targeted population are presented in Table 9. Schools targeting at-risk students produce math achievement scores that are 2.0 points lower, on average, than nontargeted charters. The gap is far greater for charters emphasizing education of students with disabilities. Charters targeting students with disabilities yield math achievement scores that are 8.0 points (over half the average annual gain) lower than nontargeted charters, holding student characteristics constant.[27] Specialized charters that focus on programs other than those targeted to at-risk and special education students possess math scores 3.8 points higher than nontargeted charters. In contrast, there are no differences in reading scores among nontargeted and the various

27. The results for charters emphasizing special education are similar when the sample is restricted to only special education students. The math-score gap for special education students in charters targeting special education students versus special education students in nontargeted charters is 8.3 points.

types of targeted charter schools. Although the estimated magnitudes differ, the restricted-value-added models yield qualitatively similar results for the effects of charter school specialization.

There are two likely explanations for the observed math achievement differentials between charters targeting special-education and at-risk students and schools that do not target these groups. First, it may be that charters targeting special-education and at-risk students place greater weight on skills that are important to these student groups but are not measured by standardized reading and math tests. For example, behavior control, development of social and oral communication skills, and vocational training may receive greater weight in these schools. Second, there is the potential for negative peer effects in these schools. Not all students who attend special-education or at-risk charters are disabled or at risk for dropping out. If disproportionally greater resources are devoted to students with disabilities and at-risk youth, or special-education and at-risk students themselves generate negative externalities, the performance of their peers in the same school may suffer.

The Competitive Effects of Charters on Student Achievement in Traditional Public Schools

To determine the competitive impact of charters on traditional public schools, a geographic information systems (GIS) database was constructed covering all public and private schools in Florida.[28] To account for the product dimension of the education market, enrollment data by grade were collected for all public and private schools in the state. This information was used to group schools into three categories: elementary (grades K–5), middle (grades 6–8), and high school (grades 9–12). Schools could be included in more than one category if they served students in more than one grade-level grouping. Using the GIS and enrollment data, the number and enrollment shares of charters, private schools, and other traditional public schools serving the same grade levels (elementary, middle, or high school) within 2.5-, 5-, and 10-mile radii of each traditional public school was determined.[29]

If charter schools and/or private schools tend to locate where traditional public schools are performing poorly, then measures of the number and size of charters and private schools would reflect not only the competitive impact

28. All charter schools, 98 percent of traditional public schools, and 91 percent of private schools were geocoded based on their street address. The remaining schools were assigned latitude and longitude values based on the centroid of their five-digit zip code.

29. The 2 percent of traditional public schools with zip-code-level geocoding were excluded as center points from the competition analysis but were included in the measures of competing traditional public schools.

of their existence but also (unmeasured) traditional public school quality. This would tend to bias downward the estimated effects of charter and private schools on student achievement in traditional public schools. To control for unmeasured time-invariant traditional school quality, a school fixed effect, θ_j (where j indexes schools), can be added to the achievement model.[30] Denoting the vector of school competition measures by $\mathbf{C}_{it}$, the achievement model becomes:

$$A_{it} = \boldsymbol{\beta}_1 \mathbf{S}_{it} + \lambda A_{it-1} + \rho C_{it} + \theta_j + \nu_i + \eta_{it}. \tag{9}$$

Direct estimation of equation (9) is problematic, since it requires inclusion of thousands of dummy variables, one for each traditional public school in the sample.[31] In order to make the problem computationally tractable, I combine the student and school fixed effects into a single effect, $\delta_{ij} = \theta_j + \nu_i$, representing each unique student/school combination or "spell."[32] Employing the assumption that $\lambda = 1$ (the restricted-value-added model) yields:

$$\Delta A_{it} = \boldsymbol{\beta}_1 \mathbf{S}_{it} + \rho C_{it} + \delta_{ij} + \eta_{it}. \tag{10}$$

Although individual and school effects are not separately identified, both individual and school heterogeneity can be eliminated by differencing the data with respect to spell means.[33]

Table 10 presents estimates of student achievement gains in traditional public schools as a function of various measures of competition. Each panel presents estimates of equation (10) using three geographic market definitions but with different measures of competition added to each. In the first two panels competition is measured by the existence of charters, private schools,

30. The school fixed effect only accounts for the time-invariant component of preexisting public school quality. If a temporary reduction in public school quality promotes the entry of new charter schools, then the measured impact of charter competition could be biased. However, given the costs of entry and exit, it seems unlikely that charters would base their entry decisions on temporary reductions in public school quality and much more likely that they would enter markets where there are persistently low-quality traditional public schools.
31. The individual fixed effects can be removed by taking differences from individual means, but that still leaves the effects of the school dummies to be estimated explicitly.
32. With very limited exceptions, charter schools in Florida must be approved by the local school district. Thus the spell fixed effects also capture any factors influencing the process of approving new charter schools.
33. Use of the restricted-value-added model is necessary to allow the use of mean-differencing to eliminate spell fixed effects. The Arellano and Bond dynamic panel data procedure used to estimate the unrestricted value-added model relies on first-differencing the data with respect to time. For a more detailed discussion of the spell-fixed-effects approach see Andrews, Schank, and Upward (2004). Standard errors for the spell-fixed-effects model are not adjusted for clustering at the school level, since the school fixed effect should account for any systematic error that is common to all students attending a particular school.

Table 10 Restricted-Value-Added Model Estimates of the Effects of School Competition on Student Achievement Gains in Traditional Public Schools (Student/School Fixed Effects)

	MATH			READING		
	2.5-Mile Radius	**5-Mile Radius**	**10-Mile Radius**	**2.5-Mile Radius**	**5-Mile Radius**	**10-Mile Radius**
One or more charters	0.488** (2.72)	0.346** (2.19)	–0.007 (0.05)	0.241 (1.29)	0.215 (1.30)	–0.103 (0.65)
One or more charters	0.485** (2.71)	0.346** (2.19)	–0.006 (0.04)	0.238 (1.27)	0.210 (1.27)	–0.099 (0.62)
One or more private schools	–0.180 (0.79)	0.067 (0.20)	0.033 (0.06)	–0.137 (0.58)	0.734* (2.10)	0.824 (1.43)
One or more other trad. public schools	0.210 (0.85)	0.053 (0.13)	0.052 (0.08)	0.230 (0.89)	0.787 (1.81)	0.249 (0.35)
Number of charters	0.372** (2.91)	0.075 (1.11)	0.025 (0.65)	0.202 (1.51)	0.028 (0.40)	–0.100** (2.51)
Number of charters	0.378** (2.94)	0.051 (0.75)	0.067 (1.63)	0.216 (1.61)	0.046 (0.65)	–0.036 (0.84)
Number of private schools	–0.025 (0.57)	0.065** (2.62)	–0.028* (1.98)	–0.105* (2.25)	–0.052* (1.97)	–0.072** (4.92)
Number of other trad. public schools	0.004 (0.05)	–0.078* (2.12)	–0.051** (2.70)	0.167* (2.13)	0.065 (1.70)	0.023 (1.16)
Market share of charters	0.075** (3.19)	–0.034 (0.94)	0.222** (4.75)	0.036 (1.50)	0.006 (0.16)	0.035 (0.73)
Market share of charters	0.070** (2.95)	–0.047 (1.27)	0.213** (4.30)	0.039 (1.60)	0.023 (0.58)	0.108* (2.12)
Market share of private schools	–0.081** (3.92)	–0.067* (2.25)	–0.016 (0.36)	–0.021 (1.00)	0.041 (1.33)	0.082 (1.78)
Market share of other trad. public schools	0.016* (2.23)	–0.016 (1.79)	–0.007 (0.55)	0.017* (2.27)	0.028** (2.98)	0.060** (4.25)
Number of students	1,707,927	1,707,927	1,707,927	1,724,793	1,724,793	1,724,793
Number of observations	2,703,494	2,703,494	2,703,494	2,723,359	2,723,359	2,723,359

Notes: Absolute values of robust t-ratios appear in parentheses. All models include time and grade dummies and a constant as appropriate. Models also include control variables reported in Table 5 and fixed effects for each unique student/school combination.

* statistical significance at .05 level, ** significance at the .01 level in a two-tailed test.

and other traditional public schools. Panels 3 and 4 use the number of alternative schools as the yardstick of competition, and panels 5 and 6 use enrollment market share to gauge the extent of competition. For each of these measures, estimates of charter competition alone as well as competition from charters, private schools, and other traditional public schools are provided.

The presence of one or more charters within a 2.5-mile radius is correlated with a 0.5 point increase in math achievement score gains. This is equivalent to a 3 percent increase in the average yearly math-score gain in traditional public schools. Consistent with the expectation that more distant schools provide less competition, the estimated impact of the presence of one or more charter schools on traditional public school math achievement gains is found to diminish with the size of the geographic market definition. The presence of one or more charters within five miles is associated with a 0.3 point increase in math-score gains, while the presence of a charter school within 10 miles has no statistically significant impact on math score gains. The results are virtually the same when controls for the existence of nearby private schools and other traditional public schools are taken into account. For reading, the point estimates of the presence of a nearby charter school on traditional public school performance are positive, but not significantly different from zero for any of the three geographic market definitions.

Each additional charter school located within 2.5 miles of a traditional public school is associated with a 0.4 higher scale-score gain in math, or 3 percent of the average math score gain. These effects diminish with the breadth of the geographic market definition and are insignificantly different from zero using either a 5-mile or 10-mile market definition. Similar results are obtained when the numbers of competing private schools and traditional public schools are added to the model. When private, charter, and traditional public school competition is taken into account, there is no statistically significant correlation between the number of charter schools and traditional public school reading achievement test scores.

Model estimates using enrollment shares as the index of competition tell a similar story. Math achievement in traditional public schools is positively correlated with charter market share for both the 2.5-mile and 10-mile market definitions, but not the 5-mile definition. For the 2.5-mile market definition, each 1 percent increase in charter school enrollment share is associated with a 0.08 increase in math score gains. Thus if charters were successful in gaining a relatively modest 5 percent market share, the model would predict increases in traditional public school achievement score gains of 0.4 points in math. For the broader, 10-mile definition, a 1 percent increase in charter school market share is associated with a 0.22 increase in traditional public school math gains. There is some evidence that charter school market share is positively correlated with traditional public school achievement scores in reading, though only for the broadest geographic market definition.

Taken as a whole, the results indicate that the introduction of charter students is correlated with modest improvements in math achievement and no reduction in reading achievement in traditional public schools. Whether the small positive net effect on math scores is due to charter competition or to positive peer effects is not clear. If charters attract better students and this worsens the pool of peers who remain in traditional public schools, then the results suggest that quality improvement triggered by charter competition more than offsets any negative peer effects. Alternatively, if charters attract a disproportionate share of disruptive or below-average students, then the math achievement gains in traditional public schools associated with charter competition may simply be due to peer effects. In either case, the evidence suggests that the existence of charter schools does not harm students who remain in traditional public schools and likely produces some net positive impacts on mathematics achievement.

5. SUMMARY AND CONCLUSIONS

As the charter school sector proliferates and more resources are devoted to building and expanding charter schools, it is important to determine what those dollars are buying. This study begins to provide quantitative evidence on the effects of charter schools on the achievement of students who attend charters as well as those who choose to remain in traditional public schools.

Consistent with other recent studies, I find that brand-new charters tend to have lower student achievement than the average traditional public school. However, of much greater importance is the long-run performance of charter schools. By their fifth year of operation Florida charter schools are found to reach a par with traditional public schools in math and to produce reading achievement scores that exceed those of the average traditional public school by an amount equal to 10 percent of the average annual achievement gain.

Charter schools are quite diverse; some are similar to traditional public schools while others seek to serve niches by targeting particular types of students (e.g., special education or at-risk students) or emphasizing particular programs (e.g., music, art, and languages). They also vary in their management structure, with most run as nonprofit entities but a significant number operated by for-profit management companies. I find that charter schools that target special education and at-risk students tend to have lower student achievement in math than nontargeted charters or the average traditional public school (holding student characteristics constant). The fact that parents willingly place their children in these schools (and keep them there) suggests that special education and at-risk charters may provide other valuable services beyond the core math and reading instruction tested on standardized exams, such as behavior management, development of social skills or oral communication skills. Management structure appears to have no impact on student achievement in charter schools; charters managed by for-profit firms perform the same as those operated by nonprofit entities.

Competition from charter schools appears to have a modest net positive impact on student achievement in Florida's traditional public schools. Whether measured by the presence of nearby charter schools, the number of competing charters, or the enrollment share garnered by charter schools, charter school competition is associated with higher math and unchanged reading scores in traditional public schools. The positive effects on math achievement are neither huge nor trivial; they are equivalent to roughly 3 percent of annual learning gains.

My findings have several important implications for the evaluation of charter schools. First, it is clear that there are significant obstacles associated with establishing a new charter school and that the performance of charter schools improves over time. Thus the age of charter schools must be taken into account when one compares their performance to traditional public schools. In Florida, charter schools operating five years or more are on par with traditional public schools in math and surpass the average traditional public school in reading achievement. Second, there is considerable diversity among charter schools. Charter schools that target specific student populations may have objectives other than simply maximizing scores on achievement tests in core subjects. Consequently, simply comparing the achievement of students in targeted charters with students in the average traditional public school may not always be appropriate. Third, it appears that competition from charter schools has a net positive impact on the performance of traditional public schools in Florida, though the size of the effect is modest. The charter sector is still rather small, however, and it is not clear how the magnitude of the competitive effects of charters will change as charter schools attract a larger proportion of the student population.

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