Are Charter School Students Harder to Educate?

Evidence from Washington, D.C.

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Abstract

One point of debate in the recent controversy in the media and among policy analysts over the academic achievement of charter school students is whether the charter students are in some way harder to educate than their counterparts enrolled in traditional public schools. In this paper we examine this question using data from the 2002-3 school year in Washington, D.C. We begin by examining a simple binomial model of the proportion of students in key demographic and programmatic categories linked to educability. We then turn to the estimation of a more theoretically appropriate mixture model that assumes two latent categories of charter schools. We conclude with an analysis that moves beyond simple demographic/programmatic factors to consider measures of educability using individual-level survey data from charter and traditional public school students.

Overall, we find little evidence of differences in the educability of students in the two sectors.

Are Charter School Students Harder to Educate? Evidence from Washington, D.C.

A report published by the American Federation of Teachers (AFT) in August of 2004 re-ignited the spirited debate over the value of charter schools as a tool to improve education in the United States (Nelson, Rosenberg, and Van Meter 2004). The report compares the performance of charter school students and their counterparts in traditional public schools using math and reading test score data from 4th and 8th grade students collected as part of the 2003 National Assessment of Educational Progress (NAEP), which is often referred to as "the nation's report card". The authors reported that, on average, charter achievement is lower, based on both average scaled scores and differences in proficiency levels, for 4th and 8th grade math and reading (although the difference in 8th grade math scaled scores was not statistically significant).

The report, which was described favorably in a front-page New York Times article (Schemo 2004), drew a swift and often heated response. Pro-school choice policy analysts, academics, think-tankers, and other partisans in the debate quickly wrote op-ed pieces, response papers, and even took out a full-page advertisement in the *Wall Street Journal* denouncing the methods and conclusions of the AFT report.[1]

One of the most repeated arguments used to counter the finding of lagging charter school performance presented in the AFT report was that the students in the charter schools are harder to educate. For example, in an op-ed piece in the *Wall Street Journal*, a group of Harvard education researchers responded to the AFT study by proclaiming: "Big deal. These results could easily indicate nothing other than the simple fact that charter schools are typically asked to serve problematic students in low-performing

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[1] A typology of the criticisms leveled at the report, along with a response from the authors, is available at http://www.aft.org/pubs-reports/closer_look/082704.htm#Bookmark6.

districts with many poor, minority children." (Howell, Peterson, and West 2004, A10).

Similarly Jeanne Allen, a noted charter advocate and president of the Center for

Education Reform, penned a response which includes a quotation from Secretary of

Education Ron Paige: "It is wrong to think of charter schools as a monolith. There are

schools for dropouts, schools for students who've been expelled, schools serving the most

economically disadvantaged families." (CER 2004).

While other aspects of the methodology of the AFT study were criticized,

including its cross-sectional nature, its use of only bivariate analysis, and the small

sample size of charter students participating in the NAEP, the claim that the population of

charter students is somehow harder to educate was the most prevalent and, perhaps, most

persuasive rejoinder to the AFT's report.[2] It is also in many ways, the most important.

The crux of the argument is that, since the charter schools really serve a different

population, it is unreasonable to hold them to the same standard as the traditional public

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[2] In her criticism of the report, Hoxby (2004) not only criticizes Nelson et al. for their methodology and choice of data, she further presents empirical evidence that the charter schools are actually outperforming their traditional counterparts on standardized achievement measures. Her method is to match each charter school to its nearest neighboring public school, both geographically and in terms of racial composition, and then compute the difference in percent proficient in math and reading at the 4th grade level on the appropriate state test. In Washington, D.C., for example, Hoxby reports that the charters outperform their competition by 35.3% or 36.6% in reading (the first number is her geographic match result, the second is the racial composition match) and 40.0% or 41.5% in math. Nelson, however, reports a variety of problems with these results in D.C., including the omission of more than half of the charter schools from Hoxby's sample, the use of different proficiency standards for the charters and comparison schools, and errors in the identification of closest neighbors (Matthews 2004). We have attempted to replicate Hoxby's findings using 2002-3 test score and demographic data from a variety of sources. Using both multiple and multivariate regression models controlling for demographic/programmatic factors, and various matching models on percentage of students eligible for free or reduced price lunch (similar to Hoxby's racial composition match but more relevant to D.C. given its demographics), we are unable to find any statistically significant evidence for a charter effect in achievement at any level of school (elementary, middle, or secondary) when considering all charter schools. In fact, given several choices of model (including several matching approaches), we find evidence supporting Nelson, Rosenberg, and Van Meter's initial report that the traditional schools are outperforming their charter counterparts. These results are available upon request from the authors.

schools—even those located in the same underserved urban school districts from which many charter schools draw their students.[3]

There is an irony in the argument that the participants in this debate have failed to notice: While charter school proponents were now claiming that charter schools are serving a *less* privileged population, opponents of charter schools have long claimed that charters served children from relatively *more* advantaged families, with more involved parents, who are easier, on average, to educate. Indeed, school choice skeptics and other researchers have long contended that any research purporting to show beneficial effects of choice reforms must be questioned on precisely this point of "cream-skimming" on the part of the charters or self-selection into choice schools by parents, and that to identify the "real" effects of charter schools after eliminating the benefits of creaming either randomized field trials must be conducted (Hoxby 2004), natural experiments should be sought (Schneider, Teske and Marschall 2000), or more advanced statistical methods must be applied (Goldhaber and Eide 2003; Schneider and Buckley 2003).

In this paper, we seek to provide evidence to help resolve this contradiction empirically. Are charter school students really harder to educate, or do they attract the most motivated or highest socioeconomic status families of their areas? Or, as we should add in the interest of completeness, do they do both? That is, are charter schools not, in Secretary Paige's words, a "monolith," but instead sufficiently heterogeneous that many charter schools choose the hardest to educate while others attract (and perhaps use strategies to retain) only the best students?

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[3] The AFT report did try to control for some factors that may reflect educability, such as free and reduced price lunch percentage and some other demographic indicators, but the data they had were limited by the NAEP "data tool" they used and their analysis was basically descriptive, leaving the report open to this charge.

The source of our data for this examination is Washington, D.C., a city we chose for several reasons. First, charter schools in D.C. represent the largest proportion of charter school pupils in any major metropolitan area; in our data from 2003, approximately 17% of public school students are enrolled in charters.[4] Also, there is prior research on this question of cream-skimming in D.C., as we will discuss below. Finally, we have been conducting a survey of parents and students in D.C. from 2001-2004, and this individual-level data will allow us to investigate the attitudinal dimension of "harder-to-educate," or educability, that is usually ignored in this literature in favor of simpler to collect demographic and programmatic information.

The plan of the paper is straightforward. After a brief review of the literature, especially the prior research on cream-skimming in charter schools in Washington, D.C., we turn to an investigation of whether charter school demographics, at the individual school level, support either side of the "harder-to-educate" debate. Next, we turn to our student-level data and examine the attitudes and peer groups of charter school students, again looking for evidence of a difference in educability. Finally, we conclude with some comments on the generalizability of our evidence and some thoughts on further research.

Creaming, Cropping, or What?

Although concerns about equity have long been a staple of the research on school choice reforms, including charter schools (e.g., Henig 1994; Smith and Meier 1995; Ascher, Fruchter, and Berne 1996), there has been relatively little research on the question of the educability of charter students. In a report released in 2000, the U.S. Department of Education, using data from 927 charter schools in the 27 states with

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[4] Recall that charter schools *are* public schools, just with significant autonomy from the traditional mechanisms of oversight and labor relations that characterize the traditional public schools.

charter laws at the time, found that the charter schools had, on average, higher proportions of black and Hispanic students (who are almost always assumed in this literature to be harder to educate), although a smaller proportion of students with disabilities or requiring special educational services (Research Policy Practice International 2000).

Others, such as Wells et al. (1998), Lopez et al. (2002) and Yancey (2000), have provided evidence that *some* charter schools do enroll proportionately more minority students, as some charter operators deliberately create schools designed to serve the particular needs of African American or Hispanic students—lending some support to the quotation from Paige cited above. This provides an arguably more positive interpretation of the often observed predilection of American parents to self-segregate their schools through residential mobility or other choice programs (e.g., Henig 1990; Schneider and Buckley 2002), although others worry that racial or ethnic segregation for any reason could have deleterious effects (Fuller 2000).

It is thus possible that any study of the educability of charter schools in the aggregate (i.e., at the national, state, or even district level), such as the 2000 Department of Education study described above, that finds differences between the charters and their traditional counterparts on racial composition or other educability proxies like proportion free/reduced price lunch or special education may be subject to a form of aggregation bias or Simpson's paradox[5] due to extreme heterogeneity across the population of charter schools.

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[5] Simpson's paradox (Simpson 1951; Blyth 1972) usually refers to the extreme case in which a relationship between variables at one level of aggregation is reversed for every subunit at a lower level of aggregation (see Pearl 2000: 173-200 for a description and illustration).

Recognizing this, Lacireno-Paquet et al. (2002) conducted a careful study of cream-skimming behavior, using data on the charter schools of Washington, D.C. in the 1999-2000 school year. They conclude that, in the aggregate, the D.C. charters in this period "are serving a population that has many characteristics associated with educational disadvantages." (2002:155). Furthermore, when they disaggregate their data into what they term "market-oriented" and "nonmarket-oriented" schools, they find some evidence that the latter are more likely to have a disproportionate share of theoretically harder to educate students. They further argue that this is not due to the market-oriented schools creaming the best students, but instead "cropping" the hardest (and most expensive) to educate. Nevertheless, they conclude that "no charter schools in the District of Columbia are serving an elite population." (2002:155).

While the Lacireno-Paquet et al. study is probably the best examination of this question to date, it still leaves several questions unanswered. First, Lacireno-Paquet et al. only measure educability using demographic proxy measures, ignoring possible differences in educability at the level of parent and student attitudes and behavior. Second, we do not know if the Lacireno-Paquet et al. findings persist in more recent years, when the number of charter schools has dramatically increased. We now turn to an empirical investigation of precisely these questions.

Examining Educability: Demographic Factors

We first examine the charter schools in Washington D.C. using the demographic and programmatic measures often cited in the educability literature: the proportion of students eligible for free or reduced price lunch, the proportion of students classified as special education students, and the proportion of students classified as English language

learners.[6] Our data come from the 2002-3 academic year.[7] Our general strategy is, for each key variable, to compare the proportion in each charter school to the average proportion in the D.C. public schools (DCPS).[8]

An important issue in an analysis of this type is how to properly model uncertainty. In one sense, we have data on the entire universe or population of D.C. charter schools and any proportions we compute are thus (in the language of classical or "frequentist" statistics) "true" parameters and not estimated quantities. However, for a number of reasons, it is desirable to model the uncertainty surrounding these values. First, although we may have population data, we have these data only for a fixed period of time, the 2002-3 academic year. If we wish to generalize our results beyond this period, we may need to account for the likely fact that our estimated values will fluctuate over time.

Similarly, but a bit more esoterically, it is possible to imagine that our population of schools and students within them are but one realization or sample drawn from a hypothetical infinite population. This "superpopulation" argument, which is often found in the sampling literature in statistics (e.g., Cochran 1946; Brewer 1963; Hartley and Sielken 1975), uses the concept of a stochastic population to re-introduce variability to

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[6] While the racial distribution across schools is often used as a further indicator of the challenges schools face in educating their students, this measure has little meaning in Washington D.C. where approximately 84% of the students are African-American.

[7] Our data for the DCPS come from a variety of sources. For our measure of free/reduced price lunch, we obtained data from the DCPS Division of Food and Nutrition Services. Data on the proportion of special education students is from the DCPS website (http://www.k12.dc.us/dcps/offices/facts1.html#14), and our data on English language learners was obtained from the DCPS Office of Bilingual Education. There are two chartering authorities in D.C., so our data on the charters comes from either the DC Public Charter School Board School Performance Reports or the DC Board of Education charter school website (http://www.dcboecharters.org/charter_schools.htm). All of our data are available on request.

[8] Nomenclature is always an issue in discussing charter schools. Charter schools are public schools and indeed approximately half of the charter schools in the District are chartered by the DC Board of Education. When we refer to DCPS, we are referring to the set of "traditional" public schools, which are organized and managed by the school district.

the quantities of interest. For example, in the literature on state politics and public policy, hypotheses are frequently tested using the population of all 50 states but standard errors are almost always reported and statistical tests of quantities of interest are reported (. Applied research in education policy (among many other areas) often implicitly adopts this approach, perhaps unwittingly. In her response to the charter school performance debate outlined in the introduction to this paper, Hoxby (2004) presents data analysis that she argues is superior to the AFT's research. One reason for this superiority, according to Hoxby, is that her data source "is not a sample: it is all charter students for whom results are reported." (2004:3). Nevertheless, she goes on to compute standard errors of her differences in achievement (which are based on a theoretical model of a sampling distribution), even going as far as to not report differences which she decides are statistically insignificant, presumably based on some level of significance selected *a priori*. Nowhere, however, is there reference to the source of the stochastic component of these data.

An alternative method to modeling uncertainty in population data can be found in the Bayesian approach to statistics. While a full description is beyond the scope of the present paper, the general idea is that Bayesian statistics are founded on a different philosophy of probability than is the more familiar, frequentist approach. To a Bayesian, probability is inherently subjective and is not necessarily defined by appeals to hypothetical infinitely-repeated trials of an experiment. In addition, under the usual Bayesian approach, the researcher need not assume that population parameters are fixed or "true" values, but instead that they can be characterized by a probability distribution.

This distribution, the posterior, is a function of both the observed data and the researcher's prior information about the parameters of interest.[9]

Our approach here to estimating the proportion of students in each charter school who are members of the various demographic groups that have been assumed to be harder-to-educate, and our related uncertainty about our estimate, is fundamentally Bayesian. Our general strategy is to treat the observed proportion of charter school students in a given category (e.g., English language learners) in a given schools as a discrete random variable modeled as the result of a binomial experiment. We assume that we have no prior information about the various quantities of interest, and we model this assumption of *a priori* ignorance using the Jeffreys (1946) prior.[10]

Specifically, let x be the number of students out of a total enrollment of n in a given school who possess a particular demographic characteristic of inference. We assume that x is distributed binomial with parameters n and π, where π is the unknown proportion of x in n. Thus:

$$p(x \mid \pi) = \binom{n}{x} \pi^x (1-\pi)^{n-x} \qquad (1)$$

It can be shown that the Jeffreys prior for this likelihood model (assuming that the prior is distributed beta, the conjugate prior to the binomial likelihood; see Lee 1997: 77-90) is:

$$\pi \sim \text{Be}\left(\frac{1}{2}, \frac{1}{2}\right) \qquad (2)$$

thus yielding a posterior probability distribution of π that is also beta:

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[9] The reader interested in more detail about Bayesian methods should consult an accessible text such as Gelman et al. (1995) or Gill (2002).

[10] A Jeffreys prior is an often desirable way to express prior ignorance because it is invariant to the scale of the unknown estimands. It thus can be used regardless of what scale we choose to measure the unknown parameters (Lee 1997: 87-88).

$$\pi \sim \text{Be}\left(\frac{1}{2}+x, \frac{1}{2}+n-x\right) \quad\quad (3)$$

We use equation (3) to estimate the posterior probability distribution of the proportion of students in each charter school who are eligible for free or reduced price lunch, classified as special education, or English language learners, independently. We present our results graphically below. Instead of presenting the entire posterior distribution for each school on each measure, we instead present the 95% highest posterior density (HPD) for each. For the current model, this region is analogous to the conventional two-sided 95% confidence interval, except that the HPD may actually be interpreted such that that the proportion of interest is in the estimated region with .95 probability.

Figure 1 here

In Figure 1 we present the estimated 95% HPD's for the proportion of students in each of 37 charter schools who are members of each of three of the demographic measures that have been linked to educability. For comparison to the DCPS, we include a vertical line at the overall proportion of traditional public school students in each category (.620 for free/reduced price lunch, .183 for special education, and .125 for English language learners).[11] Our decision rule is simple: we compare the 95% HPD of each school on each measure to the point value of the DCPS proportion on this measure. If the DCPS proportion is less than the lower bound of the charter estimate, we conclude that the charter school has more students, proportionally, in this category than the DCPS. Similarly, if the DCPS value is larger than the upper bound, we conclude that the charter

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[11] For completeness, we also estimated models separately by level of school (elementary, middle, secondary), with the appropriate DCPS comparison proportion also computed by level. The inferential results are the same as those reported below.

has proportionally fewer students in this category. Finally, if the 95% HPD contains the DPCS point estimate, we conclude that we can not distinguish between the proportions. We summarize our results in Table 1.

Table 1 here

Figure 1 and Table 1 suggest that, considering each charter school individually, many charter schools in D.C. enroll a disproportionately high number of free/reduced price lunch eligible students. On the other hand, the vast majority of charters have proportionally fewer special education and English language learning students. Our estimates provide some support for the idea that perhaps a small set charter schools are specifically targeted at these latter two groups, but most are not.

We are also interested in a test of the hypothesis that charter students are differently educable than their traditional public school counterparts on each of these measures overall, or in the aggregate. One method for conducting such a test is to return to the Bayesian conjugate beta-binomial model described above and extend it to a fully hierarchical specification (Gelman et al. 1995: 129-132). In such a model, for each of the three demographic measures, we treat each charter school as a binomial experiment for which the probability of "success" varies for each school (here of a student being a member of the category) but is drawn from a common distribution.

The problem with this approach is that we have reason to believe that the proportion in each schools is *not* drawn from a common, "monolithic" distribution. As we note above, one way of interpreting the results for special education and English language learning presented in Figure 1 is that a number of schools in D.C. are targeting these groups (this interpretation is also supported by the literature available from several

charter schools in the district and from interviews with experts on the D.C. charter

schools). To account for this data generating process, we propose instead a model that

allows for the mixture of two binomial distributions and assumes that the distribution to

which any particular school belongs is a latent (unobserved) but estimable categorization.

Our mixture model, which is adapted from a model used by Laird (1982) to

estimate batting averages for major league baseball, employs the specification discussed

in Congdon (2001: 217-8). We assume that the observed number of students x_s in a given

category in each school s is a random variable with an unknown distribution $\varphi(x_s)$ that

can be approximated as a sum of $K = 2$ binomial distributions:

$$\varphi(x_s) \cong \sum_{k=1}^{K} \theta_k \binom{n_s}{x_s} \pi_{ks}^{x_s} (1 - \pi_{ks})^{n_s - x_s}$$

That is, we assume that the charter schools are drawn from a heterogeneous population

containing two subgroups each of which is modeled with a binomial distribution with

probability of success parameter π_{ks}. The two latent subgroups or subpopulations are

mixed together with proportions θ_k (we constrain $\sum_k \theta_k = 1$). Although we recognize

that the true population of charter schools may, in fact, be composed for more than two

subpopulations, our small sample size of 37 schools (and a visual inspection of Figure 1)

suggests that limiting our model *a priori* to two groups will allow us to relax the

"monolithic" property of our simple model without sacrificing model fit or reliable

estimation.

Since our model is fully Bayesian, we also need to specify a prior distribution on

the θ_k's; we assume that they are uninformatively jointly distributed Dirichlet (the

multivariate analogue of the beta distribution). We estimate the model using Markov

Chain Monte Carlo and obtain simulations of the posterior distributions of each π_{ks} and

θ_k, as well as the posterior predictive distribution of $\varphi(x_s)$, a posterior distribution

which takes into account all sources of uncertainty in the model (see Gelman et al. 1995:

140-7).[12]

Table 2 here

We present the results of the mixture model estimation in Table 2. The table

provides the estimated posterior means and standard deviations of π_{ks} and θ_k for each of

the three outcome measures. Interpretation using these means as point estimates is fairly

straightforward. For free/reduced price lunch, for example, we estimate that the number

of students eligible in about 65.1% of the charter schools is drawn from a binomial

distribution with $\pi = .690$, while the remaining 34.9% schools have a common $\pi = .934$.

In the case of special education, it appears that the vast majority of charter schools

(84.6%) have a fairly low proportion of special education students, as reflected in their

estimated $\pi = .095$; the remaining 15.4% of schools have an estimated $\pi = .547$. Finally,

for English language learners we estimate that 69.2% of the charter schools have virtually

no students in this category ($\pi = .003$) while the other 30.8% suggest $\pi = .152$.

Figure 2 here

In the last column of Table 2, we present the 95% HPD's from the posterior

predictive distributions for each $\varphi(x_s)$, the overall mixture distribution. We also present

the entire posterior predictive distribution for each of the outcomes graphically in Figure

2. If we compared the DCPS point estimates again to these 95% HPD's, we find varying

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[12] The results presented are computed using 20,000 MCMC iterations after discarding 180,000 as burn-in.
Visual inspection of estimated posterior distributions and autocorrelations, as well as the Geweke (1992)
and the Heidelberger and Welch (1982) diagnostics do not suggest nonconvergence.

results. The mixed model suggests that the D.C. charters have, on average, proportionally more free/reduced price lunch eligible students (the lower bound on the 95% HPD is .740, which is greater than the DCPS proportion of .620). The 95% HPD for special education, however, includes the DCPS value of .183, suggesting little evidence of a difference. Finally, the DCPS proportion of English language learners of .125 is larger than the upper bound of the charter schools' 95% HPD of .0725, from which we infer that the charter schools on average enroll proportionally fewer of these students.

In sum, we find mixed evidence for a difference in educability using the demographic/programmatic data. Charter schools in D.C. may enroll, on average, more students with a lower SES background, but they have proportionally fewer English language learners and about the same fraction of special education students.

Beyond Demographics

Although we fail to find conclusive evidence that D.C. charter students are either more or less educable than traditional public school students based on an analysis of demographic and programmatic measures commonly used for this purpose, this does not necessarily indicate no *real* difference in educability. Measures such as free/reduced price lunch and special education are proxies for the real family context, peer effects, and student-level attitudes, ability, and behaviors that theoretically combine to predict a student's educability. Accordingly, we now shift our focus away from the broad demographic measures to examine a set of more precise indicators.

We examine eight key measures of educability at the individual student level. First, we look at the number of schools attended by the student. Student mobility has long been linked to negative consequences for academic achievement and progress. A variety

of empirical studies conclude that changing schools disrupts the social and academic life of students, perhaps particularly in urban areas and if caused by loss of family social resources (see, for example, Ingersoll, Scamman and Eckerling 1989; Brent and DiObilda 1993; Fitchen 1994; Wood et al. 1993; U.S. General Accounting Office 1994). However, additional research has shown that this negative effect may be offset if the move is out of an educationally disadvantaged school to a more educationally healthy environment (Brawner 1973; Lee 1951) or if the move is moderated by other factors, such as the child belonging to a military family (Cramer and Dorsey 1970). Thus, the move from an underperforming traditional public school to a charter school or other option might not be as potentially harmful as remaining in place—and the federal government certainly seems to be taking this position as evidenced by the choice provisions in the No Child Left Behind Act. However, it is reasonable to expect, on average, that excessive mobility predicts a decline in educability.

Next we look at indicators of the home environment. Since the publication of the Coleman Report, research has documented the importance of family background in predicting academic achievement. While this has often been operationally defined as socioeconomic status, here we use two sets of indicators of the non-school environment that we believe affect student performance. First, we consider the student's own expectation about her level of educational attainment, asking the student to report on the highest level of education that they expect to complete.

Next we consider measures of parental involvement with the child's education. The "effective schools" movement and a large body of subsequent work have shown the importance of such involvement. For example, Henderson (1987:1) argues that: "The

evidence is now beyond dispute: parent involvement improves student achievement. When parents are involved, children do better in school, and they go to better schools." Bryk and his colleagues have repeatedly demonstrated that parents must be involved in schooling to ensure the quality of schools as institutions serving the community. They also show that children from low-income and minority families gain the most from parent involvement (see, for example, Bryk and Schneider 2002, Bryk, Lee, and Holland 1993, or Bryk, Sebring, and Rollow 1998). Reflecting the importance of such involvement, we ask students:

- How often their parents talk to them about school;

- How much they think their parents know about school.

Finally, we consider the peer groups of the students in both the charters and the DCPS. A growing body of research has documented the importance of peer effects on learning (Coleman 1961; Bishop 1999; Nechyba 1996; Epple and Romano 1998; Hoxby 2000). One of the most disturbing findings of this body of research is how peers in many inner city schools pressure each other away into antisocial activities at the expense of learning and studying (Steinberg, Brown, and Dornbusch 1996; Betts and Morell 1999; Brooks-Gunn, Duncan, and Aber 1997). To tap peer group effects, we consider four measures:

- What proportion of a student's close friends like school;

- What proportion get good grades;

- What proportion frequently get in trouble with teachers;

- And what proportion use bad language.

To compare charter and traditional DCPS students on these measures, we use data from a telephone survey of both charter and traditional public school 7th-12th grade students conducted in Washington, D.C. in September-October, 2003.[13] The data come from the third wave of a panel survey of parents begun in the Fall of 2001. The original sample size was 1012 parents, with approximately half selected by random digit dialing and the other half, a designed oversample of charter parents, randomly selected from a list. Due to panel attrition, the restriction of student grade levels to 7th-12th grade, and the difficulty of convincing parents to allow us to interview their children, we were able to complete only 196 interviews with students.

For each of the dependent variables we estimate a model that includes, as controls, the same set of regressors:

- A dichotomous indicator for charter school enrollment; [14]

- The student's grade level (7th-12th);

- Frequency of church attendance as reported by the student (a seven category measure here treated as continuous);

- An indicator if the student reported his or her race as black;

- An indicator if English is the primary language spoken in the home;

- The parent's years of formal education;

- How long (in years) the parent has lived in D.C.;

- How long (in years) the parent has lived in the neighborhood;

- An indicator for the parent's employment status;

- An indicator for the parent's marital status, and;

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[13] During the interview period, approximately 17% of D.C. students, about 11,500, were in charter schools.
[14] Of these students, 41% were in traditional DC public schools, the remainder were in charter schools.

- The parent's reported level of satisfaction with the D.C. public schools (a
five category measure here treated as continuous).

Since our sample size is small, we are especially concerned with avoiding the loss
of any further cases due to listwise deletion of missing data. Accordingly, before
estimating our models we first predict missing values using the method of multiple
imputation (Little and Rubin 2002; Allison, 2002; King, Honaker, Joseph, and Scheve,
2001; Rubin, 1987). Specifically, we impute five complete datasets of 196 observations
each using a regression switching model (van Buuren et al. 1999) and average the results
of the analyses reported below using Rubin's (1987) method with standard errors
adjusted in accordance with Li et al. (1991).

For our first dependent variable, the total number of schools attended by the
student, we estimate the relationship between charter enrollment and the controls using
the least-squares estimator. The next set of three dependent variables—the highest level
of education that they expect to complete, how often their parents talk to them about
school, and how much they think their parents know about school—are all measured
categorically (with 6, 7, and 3 response categories, respectively). For each of these
models, then, we estimate the probability of each individual replying to each response
category conditional on the covariates using maximum-likelihood ordered logit. Finally,
for the four peer group outcome measures, we construct each proportion by dividing the
number of close friends in each category by the total number of close friends reported by
each student and then estimate the relationship between these and the covariates using
least-squares.[15]

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[15] Additional models estimated using logistic transformations of the dependent variables, as well as
specialized models for proportion data, do not alter the inferences reported below.

We report the results of the first set of models, including the estimated cutpoints

of the ordered logit models, in Table 3. As the table shows, we find a statistically

significant effect of charter enrollment only for the number of schools attended. On

average, we find that charter students have attended .48 ($p < .01$) more schools than their

traditional DCPS counterparts. This, however, is not surprising; we expect that many

charter students, unless their parents moved them to a charter at the natural break point

between elementary and middle or middle and secondary schools, have attended one

more school than their traditional public peers. Stronger evidence of a difference in

educability would be a difference in the number of schools of one or more; our 95%

confidence interval for this coefficient is [.154, .811], which we do not believe provides

support for a difference between charter and traditional public school students. We find

no differences in other measuring parental involvement estimates reported in Table 3. In

Table 4, we present the results of our four peer group regressions. Once again, we find no

statistical evidence of a difference in educability, on average, between charter and

traditional public school students.[16]

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[16] Since our sample size is small, a logical question here is whether we have sufficient power to detect any differences between the groups of students. Following Cohen's method for power analysis in multiple linear regression (Cohen 1988: 550-552), we assume a Wilk's $\lambda = .90$, a fairly small effect size of .11, 10 covariates and an α of .05, two-tailed. These parameters yield a comparison-wise power of .9953. A λ of .95 and effect size of .05 still yields a power of .8825 by this method, suggesting ample power to reject a false null even with our sample size of 196.

Are Charter School Students Different?

Both proponents and opponents of charter schools have recently argued that charter schools attract and retain different student populations than the traditional public schools—but they differ on what those different populations are.

Opponents have argued that charters, through selective recruitment and retention or through differences in parent knowledge and motivation, will be composed of easier-to-educate students from more intact, higher socioeconomic status families. More recently, charter school advocates have pointed to a presumed difference in educability in the other direction as an explanation for some recent empirical evidence that the charter schools may not be living up to their promise of higher academic achievement.

In this paper, we test these competing claims using data on the charter and traditional public schools in Washington, D.C. We find little evidence supporting either position. At the school level, looking at demographic measures of educability—proportion of free/reduced price lunch, special education, and English language learning students—our data show that there are indeed several D.C. charter schools with a higher percentage of students in each of these categories, particularly in the case of the free/reduced price lunch students. However, when considering a heterogeneous data generating process, we find mixed results: D.C. charter students, on average, appear to be more likely to be eligible for free/reduced price lunch, less likely to be English language learners, and about equally likely to be special education students.

Looking inside the schools at the student level, our survey data of charter and traditional public school students again suggest little difference on measures of attitude, parental involvement, and peer group quality. We find evidence of a difference, on

average, in the number of schools attended, but this is most likely explained by the simple fact that many charter students are expected to have switched schools one additional time.

Washington, D.C. is a politically and economically unusual city. We suspect that it is possible in theory to obtain very different empirical results than ours by considering the educability of the charter population in a larger state and by comparing this group to a statewide average. However, we believe that this would be an incorrect counterfactual comparison. In most states, charter schools remain concentrated in urban areas; any attempt to compare the educability of their students should carefully consider the relevant comparison group.

Finally, we believe that resolving the question of whether or not charter schools add value in educating their students will require hard work and careful research. The resolution of this issue will not be served by partisans (on either side of the charter school "movement") using inappropriate data and sloppy research techniques to score points in the media or in academia.

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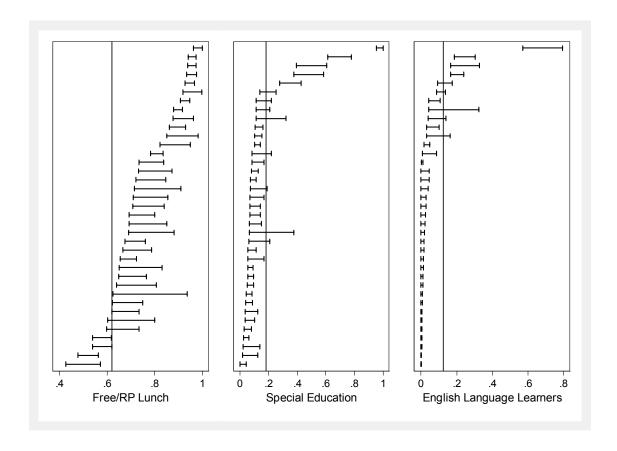Nelson, F. Howard, Bella Rosenberg, and Nancy Van Meter. 2004. *Charter School Achievement on the 2003 National Assessment of Educational Progress*. Washington, D.C.: American Federation of Teachers. Available from:

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Figure 1: 95% Highest Posterior Density intervals of the estimated proportion of students in each demographic category, using independent Jeffreys priors. Each interval represents a charter school in Washington, D.C. and is estimated using data from the 2002-3 school year. The vertical lines indicate the proportion of students in each category in the D.C. public schools overall. For visual presentation the schools are sorted independently for each measure; the same school is thus not in the same horizontal position across all three plots. Number of charter schools = 37.

Table 1: DC Charter Schools Have More Free/RP Lunch Students, but Fewer Special Education and English Language Learners.
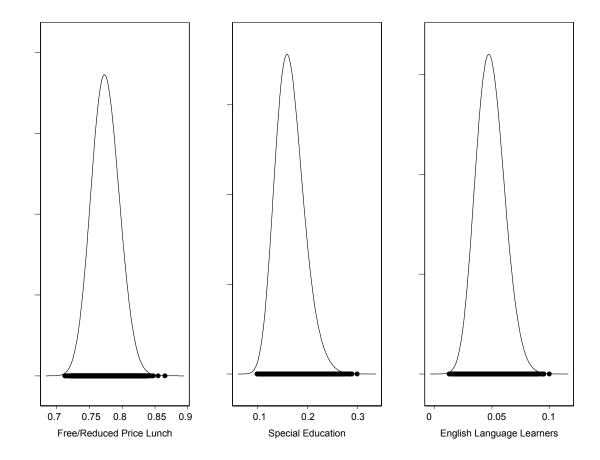
Measure of Educability	Charter > DCPS	Tie	Charter < DCPS
Free/RP Lunch	30	5	2
Special Education	5	8	24
English Language Learners	4	5	28

Results are computed from comparisons of estimated proportions for 37 DC charter schools presented in Figure 1 to DCPS point estimates of overall proportions.

Table 2: Estimated Parameters from Binomial Mixture Models of Educability
Demographic/Programmatic Factors

Measure of Educability	Posterior Mean (Standard Deviation) of π_1	Posterior Mean (Standard Deviation) of π_2	Posterior Mean (Standard Deviation) of θ_1	Posterior Mean (Standard Deviation) of θ_2	95% HPD from Posterior Predictive Distribution of $\varphi(x_s)$
Free/RP Lunch	.690 (.005)	.934 (.004)	.651 (.077)	.349 (.077)	[.740, .814]
Special Education	.095 (.003)	.547 (.022)	.846 (.056)	.154 (.056)	[.122, .223]
English Language Learners	.003 (.001)	.152 (.007)	.692 (.073)	.308 (.073)	[.029, .072]

Results are computed from MCMC estimation of Bayesian hierarchical models for proportion data from the 37 DC charter schools. Quantities of interest are computed from 20,000 iterations after discarding 180,000 as burn-in. The π_k's denote the estimated probability (or proportion) parameters of the two binomial components of the mixture. The θ_k's denote the estimates of the mixing constants (the proportion of schools in each distribution).The DCPS point estimate is contained within the 95% HPD for special education, but is below the free/reduced price lunch HPD and beyond the English language learner HPD, suggesting that the charters, on average, have fewer ELL students, more F/RPL students, and statistically the same proportion of SPED students.

Figure 2: Estimated posterior predictive densities, assuming independent binomial mixture models for each demographic/programmatic measure. Results are computed from 20,000 MCMC iterations after discarding 180,000 as burn-in. Data are number of students in each category and total enrollment for 37 D.C. charter schools in 2003.

Table 3: Charter Students Attend More Schools, On Average, But There Are Few Other Differences

	Number of Schools	*Highest Grade Expected*	*Parents Talk about School*	*Parents Know about School*
Student in Charter School	.483 (.168)***	.088 (.344)	-.123 (.326)	.271 (.378)
Grade Level	.060 (.051)	.110 (.054)**	.004 (.070)	.041 (.081)
Student's Church Attendance	-.028 (.068)	.169 (.145)	.192 (.129)	-.071 (.144)
Student Black	-.284 (.244)	.884 (.614)	.105 (.529)	-.425 (.591)
English at Home	.683 (.357)*	-.136 (.936)	.510 (.714)	.365 (1.17)
Parent's Education	-.010 (.030)	.045 (.080)	-.054 (.079)	.110 (.083)
Parent's Time in D.C.	-.030 (.026)	-.013 (.039)	-.048 (.045)	-.082 (.053)
Parent's Time in Neighborhood	-.022 (.017)	-.023 (.033)	.035 (.035)	-.002 (.033)
Parent Employed	.328 (.194)*	.295 (.477)	.564 (.438)	-.177 (.520)
Parent Married	-.202 (.205)	.993 (.480)**	.502 (.409)	.103 (.427)
Parent's DCPS Grade	-.069 (.095)	-.057 (.198)	.141 (.194)	-.096 (.211)
Cutpoint 1		-5.70 (1.84)***	-.288 (1.84)	-.435 (2.38)*
Cutpoint 2		-.826 (1.52)	-2.20 (1.86)	-.738 (2.02)
Cutpoint 3		-.480 (1.47)	-1.72 (1.82)	
Cutpoint 4		-.160 (1.48)	-1.16 (1.79)	
Cutpoint 5		1.93 (1.47)	-.311 (1.78)	
Cutpoint 6			.832 (1.81)	
Constant	3.07 (.890)***			

*** $p < .01$, ** $p < .05$, * $p < .10$, two-tailed. Number of observations = 196. Reported values are coefficient estimates with standard errors in parentheses, with all results averaged over five multiple imputation datasets (using the Li-Ragunathan-Rubin estimates of the standard errors).

Table 4: There Are No Apparent Differences Between the Peer Groups of Charter Students and Their Counterparts

	Proportion Close Friends Like School	*Proportion Close Friends Get Good Grades*	*Proportion Close Friends Get in Trouble with Teachers*	*Proportion Close Friends Use Bad Language*
Student in Charter School	.004 (.048)	-.031 (.040)	.001 (.047)	-.044 (.053)
Grade Level	.002 (.009)	.007 (.011)	-.010 (.011)	.005 (.012)
Student's Church Attendance	.017 (.018)	.013 (.015)	-.015 (.017)	-.025 (.020)
Student Black	.053 (.081)	.070 (.067)	.151 (.073)**	.010 (.087)
English at Home	-.108 (.111)	-.081 (.131)	-.124 (.098)	-.143 (.221)
Parent's Education	.005 (.011)	.017 (.010)	.007 (.011)	.012 (.012)
Parent's Time in D.C.	.004 (.007)	.007 (.007)	.001 (.006)	.007 (.008)
Parent's Time in Neighborhood	-.005 (.005)	-.005 (.004)	.007 (.005)	-.002 (.006)
Parent Employed	-.064 (.066)	-.051 (.064)	-.097 (.071)	-.040 (.074)
Parent Married	-.028 (.068)	.038 (.055)	.082 (.063)	-.0001 (.073)
Parent's DCPS Grade	.007 (.033)	-.007 (.030)	-.005 (.030)	-.002 (.037)
Constant	.757 (.239)***	.517 (.248)**	.523 (.216)**	.694 (.325)**

*** $p < .01$, ** $p < .05$, * $p < .10$, two-tailed. Number of observations = 196. Reported values are coefficient estimates with standard errors in parentheses, with all results averaged over five multiple imputation datasets (using the Li-Ragunathan-Rubin estimates of the standard errors).