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A Look at the Educational Impacts of Philadelphia Charter Schools

I. Introduction and Literature Review

Charters, schools that receive public funding but operate with some level of independence, have become an increasingly popular alternative to standard public schools in recent years. First established in Minnesota with the passage of charter legislation in 1991, today the National Center for Education Statistics reports that there are over 2 million students enrolled in over 5,700 charter schools nationwide, a number that represents about four percent of all public school enrollment. With this growth has come increased debate over charters' role in American education, with critics voicing concerns about a possible lack of accountability and transparency as well as what they see as a drive to privatize public education. Supporters of charters, however, argue that they allow for more individualized education and increase general welfare by improving all schools through market-based competition.

While policy debate is ongoing, there has been a shift towards an acceptance of and increased willingness to use charters; President Obama has repeatedly stated that charter schools are an important part of his plan to improve educational equality in the United States. Moreover, charters are often implemented in targeted urban areas that struggle to provide high quality schools; they are thought of as catalyzers for educational, economic, and cultural changes in the community. In this way, they have become central to the development efforts of a number of major cities, including New Orleans (which has replaced its entire public school system with charters, the first to do so), Detroit, and Philadelphia, the subject of this paper.

The Commonwealth of Pennsylvania passed a charter school law in 1997, and in the 18 years since Philadelphia school district has opened 67 charters that currently enroll 36,000 of the district's 131,000 students. As in many other cities, charters are seen as a possible solution to the shortcomings of the city's public school system, which have traditionally struggled to educate the city's low-income and minority students. While Philadelphia charters have at times been the subject of controversy due to their administrative practices and mismanagement, they have been popular with parents looking for alternatives, and plans continue to be made to open additional schools and convert current public schools into charters.

In light of these rapidly developing new approaches, a number of authors have studied charter schools and attempted to understand their educational and social effects.

To date, there is no consensus as to the effects charter schools have on their students and the surrounding communities. On the education front, Bettinger (2005) looked at Michigan test data to see if charters had a significant effect on test scores, ultimately concluding that charter students' test scores did not show any significant improvement compared to students in public schools. A number of other studies have conducted this kind of standardized test analysis and come to similar conclusions, but another key aspect of charters is their impact on the surrounding public schools. To this end, Booker et al. (2008) took a panel of test data and estimated a model that compared charter and public school outcomes controlling for background characteristics, finding "positive and significant effects" of charter school penetration on public school outcomes. Trachtman (2011) compared charter and public school performance in Los Angeles County using an index of academic performance, as well as looking at the competitive effects of charter schools by examining the effects of geographic proximity. He finds "evidence that…traditional public schools score higher than charter schools." And Zimmer et al. (2009) used a survey of principals and an analysis of student education outcomes to gauge the competitive threat to public schools, ultimately producing results that suggest that "California charter schools are having little effect on the climate of public schools." Nearly all the authors mentioned above stress the need for further research and investigation, as well as a nuanced consideration of the effects of different social and political environments and policies on charter success.

This paper will continue alone the path of these earlier studies in continuing to examine the relationship between charter schools and educational outcomes by applying some of previously developed models in the papers mentioned above to new data. Using Pennsylvania State School Assessment Data from 2009-2012, I will look at the standardized test results of charters and public schools to see if significant differences between the two exist. To do so, I will construct a regression based on Trachtman (2012) that models the percentage of students who score at "Advanced" or "Proficient" on the Math and Science PSSAs determined by charter status and a number of control variables. The basic equation is below:

$$TestScore_{it} = \beta_1 + \beta_2 Charter + \beta_3 X_{it} + \delta_{it} + \varepsilon_{it}$$

Charter is a dummy variable for the presence of a charter school and X_{it} a vector of control variables that include number of students tested, race, income, and student disabilities (as measured by the existence of students with Individualized Education Plans, or IEPs). δ_{it} is a vector of year fixed affects that allow for the "controlling of overall variation in results based on year." A common frustration in the literature has been the difficulty of tracking student progress on an individual level and the subsequent inability to differentiate between endogenous and exogenous change; i.e. whether the charter school is improving student performance or simply drawing higher-performing students. This selection issue is a common frustration, compounded by the fact that it is often difficult to delineate these effects using the data available. As Mills (2013) explains, different authors have taken a number of approaches to account for this. Some use random assignment to try to avoid selection bias, others that deal with larger data sets use longitudinal data and control for fixed effects to "focus on students who transferred into or out of charter schools." (Mills 236) While none of these methods are perfect, Mills believes that longitudinal data analysis with individual-level fixed effects [offer] a middle ground." In this paper, controlling by year as well as student population factors will hopefully limit these selection problems and give a more accurate look at the educational effects of charter schools. A preliminary examination of the model suggests that the time effects should be positive due to a statewide trend of rising PSSA scores; the federal No Child Left Behind Act of 2001 calls on states to make Adequate Yearly Progress (AYP), and increased focus on testing over the past decade has resulted in an increase in scores.

II. Data

The Pennsylvania System of School Assessment (PSSA) is the Pennsylvania Department of Education's measure of student success in reading, mathematics, science, and writing. It is the state's main standardized test; there is also a Keystone Exam, which was introduced in 2012 and is intended to eventually replace the PSSA. However, the Keystone is currently only administered to 11th graders, and only one year of data is available, so the PSSAs are a better fit for the purposes of this data. The state also offers a PSSA-Modified for special education students and a Pennsylvania Alternate State Assessment for students with severe cognitive disabilities, but these are represent a much smaller fraction of all test results and as such are outside the scope of this paper.

It is important to note that while the PSSA is a benchmark statistic used to measure student, school, and district progress, it is not an all-encompassing statistic like the Academic Performance Index used in a number of other states, including California and Oklahoma. This means that the PSSA dataset does not include information on exogenous factors such as student-teacher ratios or class size. While some of this information is available in public data sets like the Philadelphia School District's Open Data Initiative, this information is limited to what the district self-reports. Moreover, charters, as entities separate from the district, are not a part of this dataset, and while some cities and states have policies establishing mandatory oversight and reporting for charter schools, no such legislation exists in Pennsylvania nor Philadelphia. As a result, charter school student demographic data outside what is available on PSSA test reports is spotty and limited to what the schools have self-reported.

The Pennsylvania Department of Education has PSSA data publicly available (in some shape or form) from the 1998-1999 school year, but I will be limiting the scope of this paper to data from the years 2009-2012. I do this firstly because the volume of charter school data is much more significant in these years, and secondly due to the fact that the state data available for pre-2002 years is broader and less categorized in part because of the changes in reporting practices caused by the No Child Left Behind Act of 2001. Additionally, I am focusing on the Mathematics and Reading sections of the PSSAs— a science section was introduced for the 2007-2008 school year, but limiting my analysis to the traditional core of the test allows for more accurate comparisons. This also allows me to stay in line with previous analysis. In contrast to some of the literature mentioned above, this model draws from charter schools of all sizes and ages; the PSSA is administered in grades 3 through 8 and 11, resulting in a broad pool of student achievement. This also explains the discrepancy between the school district student totals and the number of students tested.

The Pennsylvania Department of Education offers results aggregated and disaggregated for each of the 501 public school districts in the state. For the purposes of this paper, I will be using the disaggregated data set, which gives the percentage of students who scored Advanced, Proficient, Basic, and Below Basic on the math and reading sections of the PSSA separated by grade and demographic classifiers including gender, race, and economic status. Due to student privacy policies the data set excludes groups with 10 or fewer students, which leads to gaps in some areas, especially among smaller charter schools. Still, all students are represented at least once under the “all students” group.

Table 1: Summary Table of Philadelphia School District Statistics

Year	Number Scored Math	% Advanced Math	% Proficient Math	Number Scored Reading	% Advanced Reading	% Proficient Reading
2012	70200	23.4	26.6	69970	16.1	28.9
2011	73301	30.0	28.6	73069	19.8	32.2
2010	77,423	28.8	27.5	78,063	19.0	31.0
2009	79,068	24.6	27.8	78,899	17.7	30.2
2008	80324	22.6	26.4	80098	14.3	30.6
2007	83781	18.8	26.2	83386	12	27.7

The breadth of this data set allows for widespread comparisons across time, which is a source of insight in and of itself. A look at the summary statistics in Table 1 shows that the total number of students scored in math has fallen from 83,781 in 2007 to 70,200 in 2012, the last year for which data is available. This decrease in the number of students tested is significant because this data represents only students enrolled in Philadelphia School District, of which charters are not a part. This summary data, then, shows the increased popularity of charters and serves as a helpful reminder that the aggregated PSSA data alone does not tell the complete story when comparing public and private schools.

Table 2: 2012 Charter School Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
numberscor~h	100	233.83	167.97	2	645
advancedmath	95	26.55	19.18	0	74.2
proficient~h	95	30.51	9.74	0	53.6
basicmath	95	20.22	7.99	0.9	40.9
belowbasic~h	95	22.70	19.21	0	81.8
numberscor~g	100	233.41	167.50	2	649
advancedre~g	95	18.14	12.74	0	53.6
proficient~g	95	35.47	9.34	10.4	61.9
basicreading	95	22.33	6.95	4.2	39.1
belowbasic~g	95	24.06	15.17	1.1	56.5

Table 3: 2012 School District School Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
numberscor~h	249	264.17	175.68	18	1104
advancedmath	249	20.97	16.63	0	93.8
proficient~h	249	27.23	8.38	0	47.7
basicmath	249	21.54	6.68	0.9	46.5
belowbasic~h	249	30.27	19.14	0.1	94.7
numberscor~g	249	263.35	175.15	18	1094
advancedre~g	249	14.44	13.58	0	85.5
proficient~g	249	29.45	9.73	5	55.3
basicreading	249	21.22	5.65	1.6	37.8
belowbasic~g	249	34.89	17.53	0	90

A look at the school-specific summary statistics in Tables 2 and 3 provides more useful information. As stated earlier, for student privacy reasons, Pennsylvania's Department of Education leaves blank test data for which there are fewer than ten observations. As a number of charter schools have much smaller student populations than Philadelphia public schools, this results in multiple gaps within the disaggregated school datasets, visible here in the differing number of observations among schools. Further removal of schools below a certain size from the dataset is an option, but since this paper is interested in the composition of charter schools and their effects on test scores I will leave these data points in. Moreover, a look at Charter School versus Philadelphia School District aggregated school data reveals that the size differences between charters and traditional public schools are not so great as to be insurmountable for the purposes of this analysis. As seen in Table 3, the average Charter School tested 233 students for the 2012 PSSA math section with a standard deviation of 175, not far behind the PSD's averages of 264 students with a standard deviation of 176. The main differences, then, occur at either ends of the spectrum, with no charter school as large as the largest public schools and no public school as small as the smallest charter.

Due to the lack of comprehensive disaggregated race and ethnicity statistics and the difficult and inexact nature of extracting these statistics by hand, this regression does not include the a vector of control variables. In an attempt to counteract this, this paper conducts a set of separate regressions that look solely at Black student populations to see whether the effects that charter schools have on their students varies by race.

III. Model and Results

In the first part of this paper I compare charter and school district performance through a base regression that models the percentage of a school's students who receive "Advanced" and "Proficient" grades on the PSSA in Math and Science. These initial regressions are viewable below in Tables 4-7. Each of these initial regression returned positive coefficients for the charter dummy, indicating that there is a positive relationship between the existence of a charter school and advanced or proficient test scores on the PSSA. However, a number of issues and secondary factors are present here that suggest that additional variables are needed to further refine the model and prevent us from simply concluding here.

Table 4: Initial Regression, Advanced Math

advancedmath	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
numberscoredmath	0.03	0.002	11.57	0	0.03	0.04
charterdummy	2.10	1.07	1.96	0.05	-0.01	4.22

_Iyear_2010	3.79	1.30	2.91	0.004	1.24	6.34
_Iyear_2011	4.53	1.30	3.49	0	1.98	7.08
_Iyear_2012	0.07	1.30	0.05	0.96	-2.48	2.62
_cons	13.95	1.20	11.61	0	11.60	16.31
R Squared : 0.10						

Table 5: Initial Regression, Proficient Math

proficientmath	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
numberscoredmath	0.001	0.001	0.49	0.62	-0.002	0.003
charterdummy	2.68	0.58	4.63	0	1.54	3.81
_Iyear_2010	0.056	0.70	0.08	0.94	-1.2	1.43
_Iyear_2011	1.31	0.70	1.88	0.06	-0.06	2.69
_Iyear_2012	-0.63	0.70	-0.9	0.37	-2.00	0.74
_cons	27.86	0.65	43.05	0	26.59	29.13
R Squared: 0.02						

Table 6: Initial Regression, Advanced Reading

advancedreading	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
numberscoredreading	0.02	0.002	9.05	0	0.01	0.02
charterdummy	2.50	0.86	2.91	0.004	0.82	4.18
_Iyear_2010	0.92	1.04	0.88	0.38	-1.12	2.96
_Iyear_2011	1.82	1.04	1.75	0.08	-0.22	3.85
_Iyear_2012	-1.27	1.04	-1.23	0.22	-3.31	0.76
_cons	11.13	0.96	11.62	0	9.25	13.01
R-squared: 0.07						

Table 7: Initial Regression, Proficient Reading

proficientreading	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
numberscoredreading	0.002	0.002	1.13	0.26	-0.001	0.005
charterdummy	4.48	0.62	7.17	0	3.25	5.70
_Iyear_2010	0.67	0.76	0.88	0.39	-0.82	2.15
_Iyear_2011	1.81	0.76	2.39	0.02	0.32	3.29
_Iyear_2012	-0.83	0.76	-1.09	0.28	-2.31	0.66
_cons	30.24	0.70	43.37	0	28.88	31.61
R-squared: 0.05						

First is the presence of poor R-squared values, which suggests that the chosen variables fail to explain a great deal about the model. The highest R-squared score present in these initial regressions is only .1030, indicating that the model accurately explains only about a tenth of the variance in the data. Additionally, while we generally have positive coefficients for the charter dummy, they are not all statistically significant at the 5 percent level. When we look at the fixed year effects we find for the most part the positive effects we expected, but their corresponding p-values indicate that they are not statistically significant. The final variable in this standard model is the number scored, which appears to be very weakly positive. Again, the given p-values indicate that this is only the case for the advanced regression, indicating that it does not convey a complete story.

Table 8: Skewness/Kurtosis Tests for Normality

Variable Obs Pr(Skewness)	Pr(Kurtosis)	adj	chi2(2)	Prob>chi2	
advancedmath	1.4e+03 0.0000	0.0001		.	0
proficient~h	1.4e+03 0.0000	0.0001		64.34	0
advancedre~g	1.4e+03 0.0000	0		.	0
proficient~g	1.4e+03 0.0000	0.2178		16.42	0.0003

Examining these results also shows strong signs of heteroskedasticity. A simple visual inspection of a plot of the error terms reveals widening variance as the proportion of students with higher test scores increases. This could in part be a function of the dataset and the realities of charter schools in Philadelphia: there exist a great number of charters with very few students, and these schools are typically newer and with fewer resources than more established charter and public schools. This could lead to a somewhat inflated increase in variance with an increase of students tested, which shows up as heteroskedasticity. Also of note was the lack of normality of the data; a test of the skewness of the significant variables (Table 8) showed uneven distributions. Intuitively, this makes sense: “Advanced” and “Proficient” are themselves cross-sections of what is a larger (presumably normal) distribution. It stands to reason, then, that there will not be a normal distribution of “Advanced” scores, and indeed we find a much greater number of scores on the left hand side of the distribution than on the right. A histogram of the advanced math scores shows that a much greater percentage of schools had 20% or less of their students score at advanced than had 80% percent or more score the same level. Still, heteroskedasticity is a measure of the standard errors, not the coefficient values themselves, so we can move forward while looking at the signs of the coefficients.

With this in mind, then, a useful next step was a transformation of the model to see how the coefficients respond. A logged regression is a logical next step, since we have no negative values in our data; both the percentage of students who achieve a given score and the number of students scored can obviously be no less than zero. The results, as shown in Table 9, show that some of the same issues present in the first part of this regression still exist. The charter school coefficients remain positive to weakly positive, but there are still problems with the fit of the model and the ability of the variables to explain the behavior of the model. Similarly, the year effects are largely unaffected by the move to a logged model. Under this new transformation, the "numberscored" coefficients remain positive but become statistically significant across the board. The log transformation helped produce more normal distributions within the variables, but the continued presence of low R-squared values speaks to possible omitted-variable problems.

Table 9: Logged Regression, Advanced Reading

logadvancedreading	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
lognumberscoredread~g	0.27	0.03	8.14	0	0.21	0.34
charterdummy	0.30	0.05	5.52	0	0.20	0.41
_Iyear_2010	0.12	0.07	1.84	0.07	-0.01	0.25
_Iyear_2011	0.17	0.07	2.57	0.01	0.04	0.30
_Iyear_2012	-0.04	0.07	-0.65	0.51	-0.17	0.09
_cons	0.91	0.19	4.8	0	0.54	1.29
R-squared: 0.07						

Table 10: Logged Regression, Advanced Math

advancedmath	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
numberscoredmath	0.03	0.002	11.57	0	0.03	0.04
charterdummy	2.10	1.07	1.96	0.05	-0.01	4.21
_Iyear_2010	3.79	1.30	2.91	0.004	1.24	6.34
_Iyear_2011	4.53	1.30	3.49	0	1.98	7.08
_Iyear_2012	0.07	1.30	0.05	0.96	-2.48	2.69
_cons	13.95	1.20	11.61	0	11.60	16.31
R-squared: 0.10						

From here, we can try to address the root of this omitted variable bias by introducing the control dummies and interaction terms not present in the first model. Our goal here is include the outside variables that have been shown in the literature to be strongly correlated with academic performance. The PSSA offers these variables in the disaggregated sections of their school report datasets, but in such a way that it is difficult to separate out and link with its individual school. In lieu of this, we can perform a secondary regression with these demographics separated out into their own populations. Due to the aforementioned privacy restrictions, more data exists for larger populations like female and Black students than for others. The Black student population of charter and public schools is an excellent choice for this secondary regression because of the breadth of data available due to the city of Philadelphia's demographics as a whole and due to previous literature that has found that the effects of charter schools are more positive in predominantly-black schools, a finding that has significant cultural and policy implications.

Table 11: Secondary Regression, Proportion of Black Students, Advanced Math

advancedmath	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
numberscoredmath	0.01	0.003	1.62	0.11	-0.001	0.014
charterdummy	2.30	1.031	2.23	0.03	0.28	4.33
_Iyear_2010	3.12	1.23	2.54	0.01	0.71	5.53
_Iyear_2011	3.62	1.23	2.95	0.003	1.21	6.03
_Iyear_2012	-0.87	1.23	-0.71	0.48	-3.28	1.54
_cons	18.23	1.11	16.39	0	16.05	20.41
R-squared: 0.02						

Table 12: Initial Regression with addition of percentblack variable

advancedmath	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
numberscoredmath	0.01	0.01	0.61	0.54	-0.01	0.03
charterdummy	5.92	2.55	2.32	0.02	0.89	10.94
percentblack	-0.71	0.63	-1.12	0.27	-1.97	0.54
_cons	18.66	2.31	8.07	0	14.09	23.23
R-squared: 0.22						

The results of this secondary regression, as seen in Table 11, produce much the same results as in our previous examples. We find similar statistically significant coefficients for the charter school dummy variable but a low R-squared value. The number scored coefficient turns slightly negative for the number of students who score proficient in math, but this is not statistically significant and of little information. All other coefficients maintain values similar in size and statistical significance. Again, we see similar instances of heteroskedasticity and spreading of variables, but we cannot say for certain if this is due to the nature of our data or the omitted interaction variables. Creating a new term that gives the percentage of black students in the enrolled population gives similar results, as seen in Table 12. Full fixed-year effects are not available due to difficulties in the manual extraction of the data, but we see the same lack of statistical significance and heteroskedasticity. It appears likely that the key element here is the lack of the full vector of demographic coefficients. Without these, our analysis is limited in its scope and ability to generate meaningful conclusions.

IV. Analysis and Conclusion

Though charter schools are a rapidly growing part of the American education system, the literature is still divided as to their effects on student success. This paper uses PSSA student data from 2009-2012 to analyze the impact of charter school enrollment on standardized test scores. By constructing a regression that accounts for a variety of control variables, including fixed-year effects, we determined that there exists a small positive relationship between charter schools and the proportion of students scoring at “Advanced” or “Proficient” on the Math and Reading sections of the PSSAs. The initial regression on the percentage of students who score “Advanced” on the math section, for example, produced a coefficient of 2.10 for the charter dummy. We can interpret this result as saying that charter schools are associated with an increase of 2.1 percent more students scoring “Advanced” on the Math section of the PSSA.

However, the limited scale of these regressions means that this is far from the end of the story concerning charters and their effects on student success. Pennsylvania’s lack of all-encompassing student performance variables means that we do not have full and complete racial and ethnic control variables, nor more sophisticated statistics such as teacher/student ratio. Beyond this, there are a number of possible explanations for why charters may have higher proportions of high-performing students that are not the result of better educational practices. The independent nature of charter schools means that this difference could come from something as basic as removing lower-performing students from the school, a practice that would raise their average test performance and lower the averages for the nearby public school. Moreover, there is little statistical difference in the proportion of students who score “advanced” and “proficient” in charter and public schools across subject, indicating that the distribution of scores is similar at both types of schools. We can see from this that the proportion of test scores remains similar at both kinds of schools, although charter schools are more likely to be home to extremely small student populations, which tend to do worse on the PSSAs. With all this in mind, then, we conclude by noting small correlations between charter schools and higher proportions of high-scoring students on the PSSAs, but noting that a variety of possible social, cultural, and political factors unaccounted for by this basic regression mean that further analysis is needed to more accurately gauge the differences between public and charter schools.

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