Do Charter Schools Improve Student Achievement?*

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November, 2010

Abstract

Recent reforms in education emphasize the use of charter schools as a viable strategy to improve student achievement. It is, therefore, important to understand which type of charter schools are effective. I study this question utilizing longitudinal data covering all public school students in the large urban school district of Milwaukee which has a long history of charter schools. A key challenge is that students self-select into charter schools, making it difficult to estimate the effectiveness of these schools. I find that charter schools on average have no significant effect on student achievement. This result is robust to alternative ways of dealing with self-selection, including fixed effects, propensity score matching and instrumental variables. However, I show that this average effect masks important heterogeneity in the effectiveness of charter schools across types of charter schools and students. Charter schools with higher level of autonomy from the district in terms of financial budget, academic program, and hiring decisions, are effective. I show that students in these charter schools would read at a grade level higher than similar students who attend a traditional public schools in three years. Irrespective of the type and the age of the charter school, race of the student, or grade level, attending a charter school has a positive effect on low achieving students. I show that these effects on low achieving students are substantial and are more than enough to eliminate the achievement gap in two years.

*I would like to thank Jane Cooley, Rob Meyer, Chris Taber, Karl Scholz and Carolyn Heinrich for their helpful comments and guidance. I would also like to thank the staff at Milwaukee public school district and at Wisconsin Center for Education Research, UW-Madison, for their help.

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1 Introduction

Proponents of school choice claim that choice will help students who seek to improve their educational quality, and it will also exert competitive pressure on traditional public schools to improve their quality.[1] One emerging form of school choice is charter schools. President Obama, in his education reform, "Race to the Top," rewards states which promote charter schools and encourages states and districts to create more charter schools.[2] Charter schools are public schools that are free from some of the traditional school regulations required by the state. They provide a subsidized alternative to traditional public schools (TPS) by allowing teachers to create and implement innovative educational methods tailored to their students' needs. Charter schools operate with considerably more independence than traditional public schools in terms of freedom to structure their own curriculum and school environment. For instance, many charter schools fit more instructional hours into a year or have a specific instructional style: project-based, Montessori or scripted (Hoxby et al., 2009, Angrist et al., 2009)). The number of charter schools has been growing rapidly since the first charter school law was passed in Minnesota in 1991. In 2009, they served more than 1.5 million students in 5,000 schools (Center for Education Reform, 2009).

This study uses longitudinal data covering all public schools in Milwaukee from 2005-2008 to study the effect of charter schools on student performance. However, students self-select into charter schools, making it difficult to estimate the effects of these schools on achievement. This study addresses this challenge by using alternative ways of dealing with self-selection, including fixed effects, difference-in-difference propensity score matching and instrumental variables. On average, charter schools appear to have no significant effect on student achievement. This result is robust across the estimation strategies mentioned above. However, this result masks important heterogeneity in the effectiveness of charter schools across types of charter schools and students. The main purpose of this paper is consider this heterogeneity more carefully.

The first charter school in Milwaukee was opened in 1996. By the 2008-09 school year, charter schools accounted for 21% of the total number of public schools in Milwaukee, and about 14% of the public school student population. Most of these charter schools have been operating for at least 5 years. This means that the bias associated with the initial excitement and instability of opening a charter school should be negligible. Therefore, due to the relatively large number of charter schools and their persistence over time, Milwaukee would be an ideal case for an empirical analysis of the efficacy of charters.

[1] In his book "Capitalism and Freedom" (1962), Milton Friedman proposed the use of vouchers to increase competition in the education market.

[2] Washington Post article, "Blackboard Pulpit: Encouraging the spread of charter schools," June 22, 2009. Washington Post article, "A $4 Billion Push for Better Schools: Obama Hopes Funding Will Be Powerful Incentive in 'Race to the Top'," July 24, 2009.

There are two types of charter schools in Milwaukee: "instrumentality" and "non-instrumentality" charter schools.[3] Instrumentality charter schools are instruments of the district and enjoy some of the same independence of non-instrumentality charter schools, but operate as a part of the school district, face little risk of closure and are covered by many of the same collective bargaining provisions as traditional public schools as specified by their charter. Instrumentality charter schools are unionized, and therefore, they must hire teachers from the union, but they are not required to follow the collectively bargained seniority and tenure provisions that constrain such decisions at a traditional public school. Non-instrumentality charter schools do not have to hire teachers from the union. Both types of charter schools have greater flexibility over their budgets, academic programs, and educational policies than traditional public schools, with non-instrumentality charter schools having greater autonomy than instrumentality charter schools.

The estimated effect of attending a non-instrumentality charter school on student test score gain is positive, large and significant. In contrast, the estimated effect for attending an instrumentality charter school is negative. This result complements the findings of Angrist et al., 2009. They find similar effects for Boston pilot schools which are like instrumentality charter schools. Further, I show that students in non-instrumentality charter schools would read at a grade level higher than similar students who attend an instrumentality charter school in two years, and students who attend TPS in three years. This finding suggests that the details of charter school policies matter. Charter school laws differ across states, and within states the level of charter school autonomy from school districts also varies. This could explain the mixed results about charter school effectiveness in the literature. Similarly, charter authorizers might also reasonably choose to encourage replication of these better performing non-instrumentality charter schools rather than instrumentality charter schools. This study calls for further research on the heterogeneity of charter schools and their effectiveness.

Further, this study finds that the charter schools have positive effects on previously low achieving students. This result is robust to the type and age of the charter school, race of the student and grade level. This could be another reason why there are mixed results across states and districts. For instance, if charter schools in a district target low achieving students then the results from that district could show a positive effect, assuming that district is similar to Milwaukee. Irrespective of the type of charter school, these effects on low achieving students are substantial and are more than enough to eliminate the achievement gap in two years.

Another important and unique feature of charter schools in Milwaukee is that more than 50% of the charter schools are converted from either traditional public schools or private schools. This allows me to estimate the effects of attending these conversion-

[3] Instrumentality charters are similar to Boston's pilot school program, see Angrist et al., 2009

type charter schools on student achievement. Policy makers have suggested that converting traditional public schools to charter schools would help student achievement.[4] This study finds that attending charter schools converted from traditional public schools has a negative effect on student achievement. Thus, simply converting schools to a charter school does not improve student achievement. Identifying characteristics of charter schools that are more successful at improving student achievement could help policy makers to introduce better and effective charter school policies.

The following section summarizes the previous literature on charter school evaluation. Section 3 details the Milwaukee charter school data. Section 4 develops an empirical model of student achievement and discusses the estimation issues and the empirical strategy. Section 5 presents the overall estimation results whereas Section 6 presents the results from the heterogeneity of charter schools and some robustness checks. Section 7 concludes.

2 Literature Review

The growth of charter schools in the last decade has led to a small body of research investigating whether charter schools improve student performance. Results from the existing literature are mixed, without a clear pattern across states or school districts. A key challenge in estimating the effect of charter schools is that students self-select into them. For instance, if motivated parents choose a charter school for their child to attend, then the estimated effect of attending a charter school will be biased if motivation is not controlled. One way to overcome the self-selection problem is to randomly assign students to charter schools. Such a randomized experiment has yet to be carried out.

An alternative is to take advantage of a lottery system used by oversubscribed charter schools. If a school receives more applications than it can accommodate, the school has to use a lottery system to accept students. This is random assignment, conditional on application. Using a difference-in-differences estimation strategy, Hoxby and Rockoff (2005) and Hoxby and Murarka (2009) look at oversubscribed schools in Chicago and New York, respectively, and find a positive effect of attending a charter school. Angrist et al. (2009) look at oversubscribed charter schools in Boston and also find a positive effect. Dobbie and Fryer (2009) estimate the effects of a charter elementary and middle school located in the Harlem Children's zone. They find large positive results reaching almost half of a standard deviation higher per year. A recent study done by the Mathematica policy research group (2010) evaluates 36 charter schools across 15 districts using lotteries and finds no effect, on average, of attending a charter school. However, these results from the lotteries strategy are based on a sub-sample of charter schools with wait lists,

[4]Wall Street Journal article, "Charter Schools Win a High-Profile Convert," June 24, 2009. New observer article, "Poor schools may convert to charters under bill," May 21, 2010.

and therefore are not likely to generalize to the entire charter school population. For oversubscribed schools, these effects are likely to be biased upwards compared to the effects of attending an average charter school that is not oversubscribed (Angrist et al., 2009).

In the absence of a lottery, most research has used student fixed effects to investigate whether students attending charter schools make greater achievement gains than if they had stayed in a traditional public schools. Hanushek et al. (2005), studying students in Texas, find that charter school students perform as well as traditional public school students. Bettinger (2005) finds the same result for students in Michigan using difference-in-differences estimation exploiting the variation in charter school laws. Bifulco and Bulkley (2006) summarize eight studies that used longitudinal and individual level data to estimate the effect of charter schools on student performance. In Arizona and California, the results are mixed, whereas in Florida, North Carolina and Texas, charter schools reduce scores.

Witte and Lavertu (2008), as a part of a multi-state study done by RAND, estimate the effects of attending a charter school in Milwaukee and find positive effects of attending a charter school on math test scores. This study is different from their paper in three ways. I use two different approaches in addition to fixed effects: difference-in-differences propensity score matching and instrumental variables strategy to check my findings. Second, their data is from 2000-2006, whereas this study looks at more recent years, after the test change from Terra Nova to Wisconsin Knowledge and Concepts Examination (WKCE) in 2005. It is possible that part of the change in test score gains observed for students might be due to the difference in tests. This is possible if the change in test affected the gains of some students differently than others, and normalizing might not help address this problem. Additionally, by the time of this study many charter schools have been in operation for a number of years providing me with advantage over the earlier studies. The short-term negative effects associated with organizational instability and the positive effects that come with the initial excitement of opening a charter school are less likely to be influential. Finally, there are many more student-level and school-level observations to work with than are available to Witte et al.

More recently, a study by Center for Research on Education Outcomes (CREDO) (2009) used matching strategy to compare students in charter schools to similar students in traditional public schools. They find that charter school students have slightly lower test score growth. In the absence of lotteries, I use a student fixed effects model to deal with selection bias and do robustness checks using the alternate methods of difference-in-differences propensity score matching and instrumental variables.

In terms of the heterogeneous effects of attending a charter school, studies have looked at the variation across the age of charter schools (Sass (2006), Bifulco & Ladd (2006), Booker et al. (2004), Hanushek et al. (2005)), type of charter schools (Angrist et al. (2009)), and by the race of the student (Bifulco & Ladd (2006), Booker et al. (2004), Hanushek et al. (2005)). Other than the recent study done by Mathematica (2010), no other study has looked at variation by students' previous achievement level. Further, I look at the effect for attending different types of charter schools: instrumentality and non-instrumentality charter schools as well as conversion-type and newly opened charter schools. In general, this study takes a deeper look at the heterogeneity across charter school effects.

3 Data

Table 1 presents the growth of charter schools in Milwaukee public schools (MPS) since the first charter school was authorized in 1996. After a period rapid growth of charter schools between 2000 and 2005, the net growth of charter schools in Milwaukee has slowed. By 2005, there were 40 schools in operation with 10% of the total public school student population attending a charter school. As stated earlier, many charter schools in Milwaukee have been in operation for a number of years by 2005-06 school year, which reduces the negative effects from opening a new charter school. Funding in Milwaukee for charter schools is on a per student basis.

Table 1: MPS chartering history

School Year	Total # of charters	# of charters opened	# of charters closed	Net change	% of schools as charters	% of enroll as charters
1996-1997	1	1	0	1	-	-
1997-1998	1	0	0	0	-	-
1998-1999	1	0	0	0	-	-
1999-2000	3	2	0	2	-	-
2000-2001	6	3	0	3	-	-
2001-2002	13	7	0	7	-	-
2002-2003	17	4	0	4	-	-
2003-2004	23	6	0	6	6.4%	7.4%
2004-2005	36	13	0	13	9.7%	9.0%
2005-2006	40	4	0	4	10.5%	9.9%
2006-2007	42	4	2	2	11.8%	10.2%
2007-2008	44	7	5	2	21.5%	14.3%
2008-2009	41	3	5	-3	20.5%	14.3%

Source: MPS district data.

MPS maintains longitudinal data on all public school students, including enrollment and attendance information, student demographics, test scores, and residential addresses. Table 16 in Appendix A shows the types of charter schools operating in Milwaukee for grades 3-8 along with their focus. Unfortunately, MPS has data only on charter schools they have sponsored. Therefore, there is no information on students attending non-MPS charters, which account for 25% of the charter schools. Thus, my sample is restricted to the students who attend MPS schools. If students in the non-MPS charters are different than the ones in MPS charter schools, then this might bias my estimate of the effect of attending a charter school in Milwaukee.

In the beginning of the 2005-06 school year, MPS changed their standardized test to meet the standards of the *No Child Left Behind Act of 2002-03*, which required states to test all students in reading and math in grades 3-8 and 10. The new test, called the Wisconsin Knowledge and Concepts Examination (WKCE), administered by CTB McGraw Hill, provides information for each student's achievement in math and reading during the fall school year. This study, therefore, uses data from the 2005-06 to 2008-09 school years.

Table 2: Descriptive statistics for student demographics

	All students	Ever attended Charter	Never attended Charter	Switched to charter	Switched to TPS
	Mean	Mean	Mean	Mean	Mean
Total students	39,058	6,333	32,725	2,508	1,433
% Female	49%	48%	50%	47%	47%
% F/R lunch status	84%	82%	84%	90%	91%
% ELL status	9%	12%	8%	13%	9%
% Sp Ed. status	18%	16%	18%	20%	22%
% African Am.	58%	32%	62%	41%	60%
% Asian	5%	8%	4%	4%	5%
% Hispanic	21%	37%	18%	37%	24%
% White	13%	20%	11%	14%	8%
% Mobility	38%	42%	37%	100%	100%
Charter distance	1.26	0.82	1.35	0.91	1.14
TPS distance	0.33	0.35	0.32	0.30	0.31
% Closest=Charter	14%	24%	12%	21%	21%

ELL status is a dummy which takes a value of 1 if the student is an English language learner and 0 otherwise. Sp Ed. status is a dummy which takes a value of 1 if the student is in special education and 0 otherwise. F/R lunch status is a dummy which takes a value of 1 if the student receives free or reduced lunch and 0 otherwise. African Am., Asian, Hispanic and white are dummies for race. Mobility is a dummy variable which takes a value of 1 if the student changes school from the previous year. Charter distance is the minimum distance of a charter school from the students residence. TPS distance is the minimum distance of a TPS from the students residence. Closest = charter is a dummy variable which takes a value of 1 if the closest school to the student is a charter school.

Table 2 shows descriptive statistics for students who have attended a charter school at least for a year, never attended a charter school, and students who switched between a charter school and TPS in grades 3-8 from 2005-2008. During this period, Milwaukee had about 39,000 students attending grades 3-8. Of these about 6,300 students attended a charter school for at least a year. The characteristics of students who attend charter schools are different than those of students who attend TPS. Students at charter schools are 20% white, 32% African-American, and 37% Hispanic, as compared to the 11% white, 62% African-American, and 18% Hispanic in TPS. Other charter school student demographics such as English language learner status (ELL), free and reduced lunch status (F/R lunch) and special education status, are similar to a TPS. Mobility is a dummy variable which takes a value of 1 if the student changes school from the previous year. Students attending a charter school had mobility of 42% as opposed to a mobility of 37% for students in TPS. Using the address of the student, I calculate distance to the closest charter school and TPS. The data shows that charter school students live closer to a charter school than students who attend TPS. Next, I discuss a general education model.

4 Empirical Model

Consider the following model of educational production[5]:

$$Y_{igt} = \alpha CH_{igt} + \beta' X_{igt} + \gamma_i + \xi_{igt}$$

$$\xi_{igt} = \sum_{\tau=1}^{\tau=t-1} \lambda_\tau (\alpha CH_{ig\tau} + \beta' X_{ig\tau} + \gamma_i) + \eta_{gt} + \epsilon_{igt}, \quad (1)$$

where Y_{igt} is the test score for individual i in grade g in year t, CH_{igt} is a dummy variable which indicates if individual i attends a charter school in grade g in year t, X_{igt} is the observable individual student characteristics in grade g in year t, η_{gt} is grade-year level fixed effects, and ϵ_{igt} is a random error term. The effects of school and student characteristics from previous years degrade at a rate given by (1 - λ_τ) per year.[6]

This general form of educational production function cannot be estimated because a complete set of past history is not available. Therefore, restrictions need to be placed on this model for estimation. A 'gains' model is estimated with student fixed effects and lagged covariates with $\lambda_\tau = 1$,

$$Y_{igt} = \alpha CH_{igt} + \beta' X_{igt} + \sum_{\tau=1}^{\tau=t-1} (\alpha CH_{ig\tau} + \beta' X_{ig\tau}) + \gamma_i + \eta_{gt} + \epsilon_{igt}. \quad (2)$$

Taking the first difference of equation (2) yields the following:

$$Y_{igt} - Y_{i(g-1)(t-1)} = \alpha CH_{igt} + \beta' X_{igt} + \eta_{gt} - \eta_{(g-1)(t-1)} + \epsilon_{igt} - \epsilon_{i(g-1)(t-1)}. \quad (3)$$

This model takes the average difference between the gains made by students in charter schools with the gains made by similar students in TPS. This formulation has some re-

[5]The general form of the production function presented here follows Bifulco and Ladd (2006)

[6]For a more general model of educational production function refer to Hanushek (1979).

strictions. First, the past experience of students does not deteriorate over time.[7] This implies that the effect of the quality of kindergarten has the same impact on student achievement no matter the grade.[8] The second restriction is that the unobserved effect of attending a charter school only affects the level but not the rate of growth in student achievement.

The concern with the second restriction is that if students with lower growth are more likely to choose to attend a charter school, then this selection may bias the estimate of attending a charter school using a gains model. In order to relax that restriction of the gains model, the following equation is estimated,

$$Y_{igt} = \alpha CH_{igt} + \beta' X_{igt} + \gamma_i + \sum_{\tau=1}^{\tau=t-1} (\alpha CH_{ig\tau} + \beta' X_{ig\tau} + \gamma_i) + \eta_{gt} + \epsilon_{igt}. \tag{4}$$

Taking the first difference of equation (4) yields the following:

$$Y_{igt} - Y_{i(g-1)(t-1)} = \alpha CH_{igt} + \beta' X_{igt} + \gamma_i + \eta_{gt} - \eta_{(g-1)(t-1)} + \epsilon_{igt} - \epsilon_{i(g-1)(t-1)}. \tag{5}$$

The estimator from the fixed effects model obtained from the above equation controls for any unobserved differences between students that are constant across time. The estimation of this model requires a first difference of equation (5), and thus needs three or more observations for each student. Identification in this model comes from students who transfer between charter school and TPS.[9] The model assumes that students who transfer from TPS to a charter school in the data are a representative sample of all the charter school students. If the students are not representative, then the estimator gives the local effect instead of an average effect. Therefore, I check the robustness of this result using alternate strategies in Section 6.3.

5 Average effect of attending a charter school

The results from the gains and fixed effects models of the estimation of equation (3) and (5) respectively, are explained in Table 3. The fixed effects model is the preferred model. As shown in columns (2) and (4) of Table 3, charter school students exhibit gains nearly 0.07 standard deviations smaller in reading and 0.05 standard deviations higher in math than the gains those same students would have had if they were enrolled in TPS. How-

[7] I estimate equation (3) with pre-test on the left hand side and find estimate for λ of 0.95 for math and 0.99 for reading. I cannot reject the hypothesis that $\lambda = 1$.

[8] There are several reasons it may not be appropriate to impose this assumption. For instance, the knowledge captured by the student is not durable; schools allocate resources differentially according to prior achievement; and the post-test and pre-test may be measured on different scales or the relationship between post-test and pre-test may not be linear. For a more detailed explanation, see Meyer (2006).

[9] Research show that after transferring to a new school, the test score are worse in the first year (Fowler-Finn (2001), Kerbow (1996)). Therefore, a mobility dummy is included in the regression.

ever, these estimates are not statistically significant. A potential source of bias in these models is that the choice of moving to a charter school may be due to a temporary drop in student performance. For instance, a student could draw a low-quality teacher in a TPS and perform poorly, which could lead the student to switch to a charter school. If the students' performance improves the next year (and would have even if they had stayed in a TPS), then the measured effect of charter schools will be biased upwards. Studies have shown that student mobility between schools is associated with lower student achievement (Fowler-Finn (2001), Kerbow (1996), Biernat & Jax (2000)). Identification in fixed effects model is from students who switch schools. Therefore, ignoring mobility in the regression may bias the results. The estimated effect of attending a charter school, when mobility is not controlled, increases to 0.06 from 0.05 standard deviation higher in math and to 0.05 from 0.07 standard deviation lower in reading. Further, it is important to include mobility by grade dummies in the analysis. The effect on achievement for students who change schools because of a residential move is different from the effect due to transition from elementary to middle school. Previous research (Sass (2006) and Bifulco & Ladd (2006)) show that transitions from elementary to middle school are more harmful to student achievement than general moves. I find similar negative mobility effects as the previous literature.

Table 3: Estimation results of equation (3) and (5) for the gains and fixed effect models

	Math		Reading	
	Gain	FE	Gain	FE
Charter School	0.025	0.048	-0.010	-0.065
	(0.019)	(0.041)	(0.011)	(0.041)
Mobility	0.005	0.001	0.033	0.023
	(0.029)	(0.048)	(0.024)	(0.050)
Mobility*Grade4	-0.038	-0.033	-0.034	-0.012
	(0.030)	(0.056)	(0.030)	(0.063)
Mobility*Grade5	-0.147***	-0.129*	-0.175***	-0.166***
	(0.035)	(0.067)	(0.029)	(0.059)
Mobility*Grade6	-0.051	-0.016	-0.073**	-0.060
	(0.035)	(0.061)	(0.033)	(0.061)
Mobility*Grade7	-0.020	0.049	-0.023	-0.005
	(0.039)	(0.076)	(0.033)	(0.070)
No. of Obs.	72,899	57,406	71,953	56,498
No. of Students	39,084	23,099	38,579	22,689
Adjusted R^2	0.006	0.413	0.006	0.397

-significant at 10% **-significant at 5% *- significant at 1%. Each regression includes average school demographics as well as year and grade fixed effects. The gain equation also includes the student demographics: race, sex, ELL status, special education status and free and reduced lunch status. Mobility is assigned 1 if a student changes school from the previous year. Standard errors are robust to clustering within schools.*

6 Heterogeneity of charter schools

Using the estimation strategies above, I find that, on average, the effects of attending a charter school is not statistically different from zero. However, the standard errors in Table 3 are large, and this suggests that the result masks heterogeneity in the effectiveness of charter schools. The effectiveness of charter schools may vary according to the policy environment in which the charter school operates and its characteristics, as well as the characteristics of the charter school's student population.

6.1 Analysis broken down by types and maturity of charter schools

In Milwaukee, there are two types of charter schools: instrumentality and non-instrumentality charter schools. As previously stated, non-instrumentality charter schools do not have to report to the school board. Unlike instrumentality charter schools, teachers at non-instrumentality charter schools need not be employees of the school district nor belong to the teachers' union. Non-instrumentality charter schools have a greater level of autonomy from the district not only in terms of which teachers they can hire, but also in terms of financial budget, as well as teaching curriculum as compared to instrumentality charter schools. However, non-instrumentality charter schools are held to a higher level of accountability and face a higher risk of closure. Instrumentality charter schools are usually not closed but are either merged with an existing TPS or converted to one. There are 15 instrumentality charter schools and 10 non-instrumentality charter schools in MPS as of the 2008-09 school year.

Unlike other states, a large number of charter schools in Milwaukee are converted either from TPS or private schools, in contrast to being newly established. 9 out of 15 instrumentality charter schools are converted from TPS, while 4 out of 10 non-instrumentality charter schools are converted from private schools. Table 4 shows the demographics of the students attending instrumentality and non-instrumentality charter schools. The characteristics of students who attend instrumentality charter schools are different from those of students who attend non-instrumentality charter schools. Instrumentality charter schools are 24% white, 34% African-American, and 32% Hispanic, as compared to the 3% white, 21% African-American, and 59% Hispanic in non-instrumentality charter schools. Other demographics such as English language learner status (ELL), free and reduced lunch status (F/R lunch) and special education status, are different too. Instrumentality charter schools have a lower percentage of English language learners and a higher percentage of special education students. Instrumentality charter school students are more mobile (47%) as opposed to non-instrumentality charter school students (28%). The concern is selection into school type, but given that I control for student characteristics with individual student fixed effects, these difference should not be an issue.

Table 4: Descriptive statistics for student demographics in different types of charter schools

	Instrumentality	Non-Instrumentality
Number of Students	4,921	1,449
% Female	48%	49%
% F/R Lunch status	80%	88%
% ELL status	10%	24%
% Sp Ed. status	17%	12%
% African Am.	34%	21%
% Asian	6%	16%
% Hispanic	32%	59%
% White	24%	3%
% Mobility	47%	28%

ELL status is a dummy which takes a value of 1 if the student is an English language learner and 0 otherwise. Sp Ed. status is a dummy which takes a value of 1 if the student is in special education and 0 otherwise. F/R lunch status is a dummy which takes a value of 1 if the student receives free or reduced lunch and 0 otherwise. African Am., Asian, Hispanic and white are dummies for race. Mobility is a dummy which takes a value of 1 if the student changes school from the previous year.

First, I estimate if more autonomy from the district leads to better student outcomes. As seen in the upper half of Table 5, non-instrumentality charter schools have a positive effect on their students in reading, while instrumentality charter schools have a negative impact on their students. A student who attends a non-instrumentality charter school improves over their counterpart in an instrumentality by one-quarter of a standard deviation. The difference between these two estimates is statistically significant at the 5% significance level. One standard deviation corresponds to 50 test score points. The difference between two grades in elementary school corresponds to 25 point on the test. Thus, students at a non-instrumentality charter school would be reading at a grade higher from their counterparts in an instrumentality charter school in two years, and their counterparts in a TPS in three years. This is an important result of the paper. Angrist et al. (2009) find larger effects for their comparison between charter schools and pilot schools in Boston. Charter schools in Boston correspond to non-instrumentality charter schools in Milwaukee, and pilot schools in Boston correspond to instrumentality charter schools in Milwaukee. These results indicate that charter schools with more autonomy from the district are effective. The result also shows that charter schools that are converted from traditional public schools are less effective.

The lower half of Table 5 shows the result of the effect of attending a mature charter school. Since some of these charter schools are converted from TPS or private school; a dummy for those conversions are included in the regression. As most empirical studies (Booker, et al. (2004), Bifulco & Ladd (2006), Sass (2006)) have found a positive relationship of effect with school's maturity, I obtain similar results. However, the difference between the coefficients of older and newer charter schools is not statistically significant

Table 5: Summary of results for types and maturity of charter schools

	Math	Reading
Instrumentality	0.034	-0.073*
	(0.040)	(0.042)
Non-Instrumentality	0.128	0.195**
	(0.093)	(0.088)
Converted from TPS	0.007	-0.069*
	(0.088)	(0.041)
Converted from Private	0.006	0.013
	(0.045)	(0.056)
$Age \geq 3$	0.121*	0.048
	(0.062)	(0.097)
$Age < 3$	0.036	-0.051
	(0.049)	(0.044)
Converted from TPS	-0.071	-0.170*
	(0.076)	(0.096)
Converted from Private	-0.057	-0.030
	(0.061)	(0.099)

-significant at 10% **-significant at 5% *- significant at 1%. The fixed effects models are estimated from equation (5) using dummy variable for instrumentality and non-instrumentality charter schools. The regressions include mobility per grade dummy, average school characteristics and year and grade fixed effects. Standard errors are robust to clustering within schools.*

at the 10% significance level in math or reading. Again, the results show that charter schools that are converted from traditional public schools are less effective. Policy makers have suggested converting TPS to charter schools to improve low achieving schools.[10] This result shows that simply converting schools does not improve student performance.

Thus, in this sub-section, I show that charter schools with higher level of autonomy from the district are effective and charter schools converted from TPS are not effective.[11]

6.2 Analysis broken down by types of students

6.2.1 Analysis broken down by race

Charter schools may target and help different types of students. Therefore, I estimate the differential impact of attending a charter school by student race characteristics. Charter schools show distinctly different results for different minority students. Table 6 separates the effect of attending a charter school for African-American, Hispanic and white

[10]Wall Street Journal article, "Charter Schools Win a High-Profile Convert," June 24, 2009. New observer article, "Poor schools may convert to charters under bill," May 21, 2010.

[11]One needs to be careful about the interpretation of the second result. It might be the case that charter schools, which are converted from TPS, might be worse off if they were not allowed to convert. That counter factual is not available to test in my case.

students. As seen in Table 6, Hispanic students attending a charter school perform worse than their TPS peers, whereas African-American and white students perform better. Results from the student fixed effects model indicate that Hispanic students in charter schools have a negative gain of 0.14 standard deviations in reading. African-American students in charter schools have positive growth of 0.12 and white students have positive growth of 0.13 in math. However, the difference between the coefficients for the different races in math is not statistically significant at the 10% significance level, whereas the difference between the coefficients in reading is statistically significant at the 10% significance level.

Table 6: Summary of results for Hispanic and African-American students

	Math	Reading
African-American	0.117**	-0.002
	(0.057)	(0.061)
Hispanic	0.012	-0.135**
	(0.045)	(0.049)
White	0.128*	-0.030
	(0.075)	(0.040)

-significant at 10% **-significant at 5% *- significant at 1%. The fixed effects models are estimated from equation (5) using dummy variable interaction of Hispanic*charter and African-American*charter white*charter respectively.The regressions include mobility per grade dummy, average school characteristics and year and grade fixed effects. Standard errors are robust to clustering within schools.*

The negative effect for Hispanic students possibly might be because 45% of Hispanic students who attend charter schools choose schools with English as a second language (ESL) or bilingual (Spanish) programs. Table 7 presents the results of the effect of attending a charter school with ESL program on the reading scores for Hispanic students. The result shows that charter schools with ESL programs perform better in reading. The negative effect of attending a charter school is for Hispanics attending non-ESL charter schools. Similarly, I estimate the effect of attending a charter school for English language learners (ELL). I find that the significant negative effect is due to these ELL students. This result suggests that Hispanic ELL students are performing worse at a charter school than if they would have chosen to attend a TPS. This could be either a selection story; these students are selecting the wrong school to attend, or that the charter schools that these students attend put emphasis on curriculum and skills unrelated to test scores.

Table 7: Summary of results for Hispanic students in ESL programs or their ELL status

	Reading
ESL programs	-0.081
	(0.06)
Non-ESL programs	-0.123**
	(0.059)
Non-ELL students	-0.075
	(0.062)
ELL students	-0.154**
	(0.077)

-significant at 10% **-significant at 5% *- significant at 1%. The fixed effects models are estimated from equation (5) using dummy variable interaction of ESL programs or ELL status for Hispanics students in reading. The regressions include mobility per grade dummy, average school characteristics and year and grade fixed effects. Standard errors are robust to clustering within schools.*

6.2.2 Analysis broken down by achievement

Most education policies are introduced to help improve low-achieving students' performance and to reduce the achievement gap (The *No Child Left Behind Act of 2002-03*). Therefore, in this subsection, I investigate if the different types of charter schools help low-achieving students to improve performance. In order to estimate this effect, students are divided into groups depending on their previous test score (with respect to the district mean for that particular grade and year). Table 8 shows the effect of attending a charter school for high and low-achieving students. In the upper half of the table, analysis is done if the previous test score is above or below the district mean, whereas in the bottom half, the analysis is done using quartiles. Irrespective of the analysis done, attending a charter school improves test score gains for low achieving students in math and reading, whereas high achieving students do worse when they attend a charter school. Moreover, the difference in impacts between high and low achieving students is statistically significant at the 1% significance level for math and reading. The only other paper which looks at the effect of attending a charter school for low achieving students is the Mathematica study (2010). However, they look at oversubscribed schools, which possibly have more advantaged students than in the case of Milwaukee. If charter schools are suppose to help improve outcomes of low achieving students, then Milwaukee would be a better setting to estimate that effect. Recent studies (Angrist et al. (2009), Angrist et al. (2010), Nicotera et al. (2009)) find similar large overall effects in other urban districts.

One of the possible reasons that there is a large effect on low-achieving students, could be the added level of accountability of having their charters revoked. Charter schools need to show adequate yearly progress as opposed to a traditional public school, otherwise their charter would not be renewed. This might foster a program of teaching to the low achieving students, as charter schools might find it easier to improve their test scores. High performing students would then suffer at these schools which might explain the negative effect for these students.

Table 8: Summary of results for low achieving and high achieving students in charter schools

	Math	Reading
Low achieving students	0.368***	0.212***
	(0.046)	(0.052)
High achieving students	-0.237***	-0.295***
	(0.048)	(0.041)
1st quartile (Bottom)	0.643***	0.510***
	(0.081)	(0.075)
2nd quartile	0.163***	-0.032
	(0.058)	(0.053)
3rd quartile	-0.156***	-0.246***
	(0.055)	(0.053)
4th quartile (Top)	-0.569***	-0.573***
	(0.096)	(0.072)

-significant at 10% **-significant at 5% *- significant at 1%. The fixed effects models are estimated from equation (5) using dummy variable interaction of low achievement*charter and high achievement*charter, where low achievement is a dummy variable, assigned a value of 1 if previous test* < 0 *and high achievement is a dummy variable, which is assigned a value of 1 if previous test* > 0. *The regressions include mobility per grade dummy, average school characteristics and year and grade fixed effects. Standard errors are robust to clustering within schools.*

The results from Table 8 show the overall effects of attending a charter school for low and high achieving students. However, I have shown that there is considerable heterogeneity in the effectiveness of charter schools. Therefore, I check the robustness of the above result across the different types of charter schools. On average, there is a positive effect of attending a non-instrumentality charter school and a negative effect of attending an instrumentality charter school. Table 9 identifies the separate effects of the charter school types for both low and high achieving student groups. The positive effect of attending a charter school for low achieving students holds for both types of charter schools. However, the effect for low achieving students is greater in the case of non-instrumentality charter schools in both math and reading. The difference in the coefficient for low achieving students attending instrumentality and non-instrumentality charter schools is not statistically significant for math, but it is statistically significant for reading at the 10% significance level. This could possibly be because non-instrumentality charter schools face more stringent accountability requirements than instrumentality charter schools. Non-instrumentality charter schools face a real threat of being closed, whereas instrumentality charter schools are either merged with an existing TPS or converted to one. The bottom half of Table 9 performs similar analysis but separates those converted from TPS and private schools. Similar results are obtained. Usually, one would expect better private schools to convert to a charter school

Table 9: Summary of results for low achieving and high achieving students in different types of charter schools

	Math	Reading
Low achieving at Instrumentality	0.337***	0.153***
	(0.051)	(0.053)
Low achieving at Non-Instrumentality	0.464***	0.509***
	(0.093)	(0.099)
High achieving at Instrumentality	-0.217***	-0.301***
	(0.052)	(0.044)
High achieving at Non-Instrumentality	-0.321***	-0.158*
	(0.082)	(0.082)
Low achieving at Instrumentality	0.323***	0.159***
	(0.072)	(0.055)
Low achieving at Converted from TPS	0.351***	0.132*
	(0.093)	(0.069)
Low achieving at Non-Instrumentality	0.459***	0.503***
	(0.124)	(0.128)
Low achieving at Converted from Private	0.472***	0.522***
	(0.076)	(0.098)
High achieving at Instrumentality	-0.197***	-0.261***
	(0.061)	(0.046)
High achieving at Converted from TPS	-0.241***	-0.357***
	(0.071)	(0.049)
High achieving at Non-Instrumentality	-0.307***	-0.154*
	(0.088)	(0.087)
High achieving at Converted from Private	-0.335***	-0.157**
	(0.069)	(0.079)

-significant at 10% **-significant at 5% *- significant at 1%. The fixed effects models are estimated from equation (5) using dummy variable interaction of low achievement*charter and high achievement*charter, where low achievement is a dummy variable, assigned a value of 1 if previous test < 0 and high achievement is a dummy variable, which is assigned a value of 1 if previous test > 0. The regressions include mobility per grade dummy, average school characteristics and year and grade fixed effects. Standard errors are robust to clustering within schools.*

since by converting, they would increase the level of scrutiny from the district. This is reflected in these schools having the largest positive effects.

Next, I estimate if charter schools help certain types of low achieving students. For each race, I divide the sample of students attending a charter school according to their pre-test level with respect to the district mean for that grade. Table 10 presents the results for low achieving and high achieving students for different races. The effects for low achieving students is still positive, regardless of race. The coefficients for African-Americans and Hispanics differ because there is a higher percentage of African-Americans and whites (34%) in the lowest quartile than Hispanics (21%) at charter schools. As seen in Table 8, students in the lowest quartile have larger positive effects than those in the

Table 10: Summary of results for low achieving and high achieving students in charter schools

	Math	Reading
Low Achieving Hispanic students	0.366***	0.132*
	(0.065)	(0.077)
Low Achieving African-American students	0.360***	0.227***
	(0.074)	(0.083)
Low Achieving White students	0.584***	0.474***
	(0.138)	(0.064)
High Achieving Hispanic students	-0.269***	-0.329***
	(0.066)	(0.061)
High Achieving African-American students	-0.274***	-0.312***
	(0.084)	(0.064)
High Achieving White students	-0.055	-0.186***
	(0.073)	(0.053)

-significant at 10% **-significant at 5% *- significant at 1%. The fixed effects models are estimated from equation (5) using dummy variable interaction of low achievement*charter and high achievement*charter, where low achievement is a dummy variable, assigned a value of 1 if previous test < 0 and high achievement is a dummy variable, which is assigned a value of 1 if previous test > 0. The regressions include mobility per grade dummy, average school characteristics and year and grade fixed effects. Standard errors are robust to clustering within schools.*

second lowest quartile, which may explain these differences in the effects for race.

Table 11: Summary of results for low achieving and high achieving students in charter schools

	Math	Reading
Low Achieving at charter school with $Age < 3$	0.346***	0.200***
	(0.072)	(0.057)
Low Achieving at charter school with $Age \geq 3$	0.445***	0.335***
	(0.077)	(0.095)
High Achieving at charter school with $Age < 3$	-0.222***	-0.263***
	(0.055)	(0.042)
High Achieving at charter school with $Age \geq 3$	-0.188***	-0.205**
	(0.065)	(0.086)
Converted from TPS	-0.071	-0.156*
	(0.070)	(0.084)
Converted from Private	-0.060	-0.032
	(0.065)	(0.088)

-significant at 10% **-significant at 5% *- significant at 1%. The fixed effect models are estimated from equation (5) using dummy variable interaction of low achievement*charter and high achievement*charter, where low achievement is a dummy variable, assigned a value of 1 if previous test $< 0$and high achievement is a dummy variable, which is assigned a value of 1 if previous test > 0. The regressions include mobility per grade dummy, average school characteristics and year and grade fixed effects. Standard errors are robust to clustering within schools.*

Table 11 revisits the previously discussed effects of low achieving students' attendance of charter schools, but separates it by the level of maturity of the charter school attended. As expected, low achieving students attending charter schools at higher level of maturity have larger positive effects in both math and reading than those attending newly opened charter schools. However, the difference in impacts between lower achieving students at charter schools with age < 3 and at charter schools with age ≥ 3 is statistically insignificant.

Table 12: Summary of results for low achieving and high achieving students in charter schools

	Math		Reading	
	Elementary	Middle	Elementary	Middle
Low achieving students	0.267**	0.259***	0.274*	0.392***
	(0.117)	(0.094)	(0.149)	(0.102)
High achieving students	-0.454***	-0.425***	-0.249**	-0.305***
	(0.127)	(0.108)	(0.116)	(0.078)

-significant at 10% **-significant at 5% *- significant at 1%. The fixed effects models are estimated from equation (5) using dummy variable interaction of low achievement*charter and high achievement*charter, where low achievement is a dummy variable, assigned a value of 1 if previous test* < 0 *and high achievement is a dummy variable, which is assigned a value of 1 if previous test* > 0. *The regressions include mobility per grade dummy, average school characteristics and year and grade fixed effects.*

Lastly, the effect is estimated across elementary and middle schools. Table 12 shows the results of attending an elementary or a middle school that is a charter school. Low achieving students make more improvement than high achieving students at elementary as well as middle schools that are charter schools. Thus, the result is robust to multiple specifications; low-achieving students perform better when they attend charter schools regardless of school type, school maturity, student race, or grade level. Thus, charter schools are better at improving achievement for low performing students.

6.3 Robustness checks of the average effect

6.3.1 Difference-in-difference propensity score matching

A fixed effects approach mitigates the impact of selection bias by controlling for unobserved characteristics that do not change over time. Three years of data are required to estimate the effects of attending a charter school using a fixed effects strategy. It also limits the analysis to students who switch. Thus, if the students who switch differ significantly from the students who attend a charter school, then the marginal average treatment effect is estimated instead of an average effect. Therefore, instead of using student fixed effects for analysis, some research has used propensity score matching (CREDO, 2009). A difference-in-difference matching approach uses observed covariates to deal with self-selection without imposing a functional form on test score gains. I estimate the effects of attending a charter school using difference-in-difference propensity score matching estimator, proposed by Heckman et al. (1997, 1998) to check for robustness of the overall effect. A brief explanation of this model is in Appendix B. Appendix C shows the result of the propensity score estimation.

The effect of attending a charter school is estimated using different matching techniques: radius caliper, kernel and neighborhood matching. After the students are matched, the differences in test score gains are calculated, along with bootstrapped standard errors.[12] Further, I impose a common support requirement, dropping all those students for whom no match exists. This common support assumption will bias the results if there is not significant overlap. In each of the models, there is significant overlap in the distribution of propensity scores except for the case of radius caliper with $\sigma = 0.0001$. Figure 1 in the Appendix D shows the distribution of the log odd ratios for the treated and the control groups in the case of radius caliper with $\sigma = 0.01$. An example of balancing between the covariates using radius caliper matching with $\sigma = 0.01$ for math gain scores is presented in Appendix E. [13]

Table 13 presents the estimated average treatment of the treated effects of attending a charter school on gains in reading and math test scores. There is a positive effect in the changes in math test scores and negative effect in reading test scores gains but these effects are insignificant. The effect varies from 0.029 to 0.042 and from -0.016 to -0.020 for math and reading gains, respectively.

However, matching methods are not robust against "hidden bias" arising from unobserved variables which affect assignment to treatment and outcome. Instrumental variable estimation provides an alternative strategy for the estimation of attending a charter school, which is discussed next.

[12] In the light of recent work by Abadie & Imbens (2006) suggesting that bootstrapping gives incorrect standard errors with nearest neighbor matching, linear matching methods are used to also validate the result.

[13] Wooldridge (2009) shows that for estimating a constant endogenous treatment effect, matching on covariates that satisfy instrumental variables assumptions increases bias in the case of propensity score matching. The model without the distance covariates is estimated, and I still obtain similar results.

Table 13: Estimated Average Treatment of the Treated Effects of Attending a Charter School on Math and Reading test score gains using a Difference-in-Difference Propensity Score Matching analysis

Matching Strategy	Charter Effect	Std Error	Off Support	Balancing issue
Math				
Radius Caliper				
($\sigma = 0.01$)	0.030	(0.020)	5	-
($\sigma = 0.001$)	0.030	(0.018)	20	*Charter distance*
($\sigma = 0.0001$)	0.030	(0.021)	228	*Charter distance*
Local Linear Reg				
Kernel(epan)	0.029	(0.018)	5	*Charter distance*
Kernel Regression				
(epan)	0.029	(0.021)	5	-
Neighborhood				
N=5	0.029	(0.018)	0	-
N=3	0.032	(0.024)	0	-
N=1	0.042**	(0.020)	0	*Charter distance*
Reading				
Radius Caliper				
($\sigma = 0.01$)	-0.016	(0.014)	5	-
($\sigma = 0.001$)	-0.016	(0.012)	23	*Charter distance, charter distance*^{2}
($\sigma = 0.0001$)	-0.020	(0.014)	287	*Charter distance*
Local Linear Reg				
Kernel(epan)	-0.016	(0.016)	5	*Charter distance*
Kernel Regression				
(epan)	-0.016	(0.014)	5	-
Neighborhood				
N=5	-0.020	(0.017)	0	-
N=3	-0.020	(0.018)	0	*Asian*
N=1	-0.019	(0.018)	0	*Charter distance, Asian*

-significant at 10% **-significant at 5% *- significant at 1%*

6.3.2 Instrumental variables strategy

Starting with the general model and using the same restrictions as in the gains model, the following equation is reached as shown in equation (3).

$$Y_{igt} - Y_{i(g-1)(t-1)} = \alpha CH_{igt} + \beta' X_{igt} + \varsigma_{igt} \quad (6)$$

In this case, I assume that attending a charter school is correlated with the error term even after conditioning on observed covariates, X_{igt}. For instance, if students with motivated parents move to a charter school, and assuming that these parents have a greater impact on their children's achievement, then parental motivation would create an upward bias in the effect of attending a charter school.

In order to deal with this endogeneity issue, an exogenous variable which affects the decision of attending a charter school but not achievement is needed. Most student characteristics that influence attending a charter school, such as income, attitude of the student, and motivation of the students' parents, are also likely to influence student achievement. Moreover, characteristics of charter schools that influence attendance, such as school policy, are likely to be related to the effectiveness of the school. Proximity to a charter school can be used as an exogenous variable that does not influence student achievement (Card, 1993). Students who live farther away from a charter school face additional transportation costs. As seen from the descriptive Table 2, students who live closer to a charter school are more likely to attend a charter school. The effects using the instrumental variable approach are inconsistent if the instruments are correlated with the residuals. For instance, if motivated parents decide to live closer to a charter school, then the proximity to a charter school would be an inconsistent instrument. However, the data does not show any significant changes in addresses of students before they attend a charter school. According to an MPS administrator, many of the charter students do not even know that they are attending a charter school. Moreover, thirteen out of the twenty-five elementary and middle charter schools were converted from either traditional public or private schools.

Using an instrumental variable approach, I proxy for charter school attendance using distance to the closest charter school, TPS and a dummy (*Closest is Charter*) that takes a value of 1 if a charter school is the closer than TPS. As attending a charter school is endogenous and binary, I model the first stage binary response model using a probit model as $Pr(CH_{igt} = 1) = \Phi(\delta' Z_{igt} + \beta' X_{igt} + \eta_{gt} + \epsilon_{igt})$, to obtain fitted probabilities $Pr(\widehat{CH_{igt} = 1})$. Equation (6) is estimated using $Pr(\widehat{CH_{igt} = 1})$ as an instrument for attending a charter school. (Wooldridge, 2002)

The estimates from the first stage binary response model using a probit model, $Pr(CH_{igt} = 1) = \Phi(\delta' Z_{igt} + \beta' X_{igt} + \eta_{gt} + \epsilon_{igt})$, are shown in Table 8. As the distance from the charter school increases, the probability of attending a charter school decreases. It is opposite in the case of the distance from the closest TPS, as expected. Similarly, if the closest school is a charter school, then the probability of attending a charter school increases. In the case of a single endogenous variable, the Kleibergen and Paap statistic to test the weakness of the instruments, reduces to a joint F-test of the significance of the instruments in the first stage (according to Staiger and Stock (1997) and Stock and Yogo (2005), the critical value of F-stat of the IV in first stage is 10). The results indicate that distance to the closest TPS and charter school are weak instruments. However, the F-stat for the *Closest is Charter* dummy is 32.7, which passes the weakness test. [14]

[14]Therefore, results from weak instruments are dropped from the remaining tables but are available from

Table 14: Results from probit as the first stage as $Pr(CH_{igt} = 1) = \Phi(\delta' Z_{igt} + \beta' X_{igt} + \eta_{gt} + \epsilon_{igt})$

	(1)	(2)	(3)	(4)	(5)
Charter distance	-0.12*	-0.26**	-0.21**	-0.476**	
	(0.06)	(0.09)	(0.09)	(0.08)	
$(Charter\ distance)^2$		0.01**		0.059**	
		(0.00)		(0.016)	
TPS distance			0.251**	0.344**	
			(0.092)	(0.101)	
$(TPS\ distance)^2$				-0.071**	
				(0.019)	
Closest is charter					0.37***
					(0.07)
$PsuedoR^2$	0.30	0.31	0.31	0.29	0.30
F-stat	7.71	23.37	8.53	38.86	32.7

-significant at 10% **-significant at 5% *- significant at 1%. Student demographics, average school characteristics and dummies for mobility, grade and year were included in the regression. Mobility is assigned 1 if a student changes school from the previous year. Charter distance is the minimum distance of a charter school from the students residence. TPS distance is the minimum distance of a TPS from the students residence. Closest is charter is a dummy which takes a value of 1 if the closest school to the student is a charter school. Critical value of Staiger and Stock on excluded instrumental variables in first stage is 10.*

Table 15 shows the effects of attending a charter school for math and reading estimated by the IV strategy explained above. The different columns in the tables represent the different combinations of instrumental variables used. In the case of math, the effect is positive but insignificant. In the case of reading, the effect of attending a charter school is not statistically different from zero. Thus, going to a charter school has no significant affect on achievement according to the instrumental variables strategy.

Next, I check if the instruments are uncorrelated with the residual. This can be tested by including the instruments in the second stage of IV approach. The results of that approach, presented in the Table 15, show that the instruments are not correlated with the error term. Finally, a Hausman test to check the endogeneity of attending a charter school is calculated. The null hypothesis is that the estimator from a gains model is consistent and efficient. In all the cases, the test cannot reject the null hypothesis that attending a charter school may be treated as exogenous. Other robustness checks of the instrumental variable approach are explained in Appendix F.

Hence, the conclusion from all these strategies is that on average attending a charter school has no significant effect on test score gains. However, as shown in Sections 6.1 and 6.2, this result masks the heterogeneity in the effectiveness of the different types of charter schools and their effectiveness on different types of students.

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the author upon request.

Table 15: Results from probit as the first stage and using the predicted probability as an IV for Math

	(1)	(2)	(3)	(4)
		Instruments used		
Charter Distance	X		X	X
$(Charter\ distance)^2$	X		X	
TPS distance			X	X
$(TPS\ distance)^2$			X	
Closest is Charter		X		X
		Math		
Charter Effect	0.030	0.025	0.027	0.030
	(0.063)	(0.064)	(0.062)	(0.060)
Including instruments in second stage to test if $E(Z'u) = 0$	Uncorr.	Uncorr.	Uncorr.	Uncorr.
Hausman test *(p-value)*	0.37	0.69	0.62	0.40
		Reading		
Charter Effect	-0.010	-0.004	-0.006	-0.009
	(0.047)	(0.047)	(0.046)	(0.045)
Including instruments in second stage to test if $E(Z'u) = 0$	Uncorr.	Uncorr.	Uncorr.	Uncorr.
Hausman test *(p-value)*	0.76	0.76	0.79	0.86

-significant at 10% **-significant at 5% *- significant at 1%. Student demographics, average school characteristics and dummies for grade and year were included in the regressions. Mobility is assigned 1 if a student changes school from the previous year. Charter distance is the minimum distance of a charter school from the students residence. TPS distance is the minimum distance of a TPS from the students residence. Closest is charter is a dummy which takes a value of 1 if the closest school to the student is a charter school.*

7 Conclusion

Recent reforms in education emphasize the use of charter schools as a viable strategy to improve student achievement. Results from the existing literature are mixed, without a clear pattern across states or school districts. I estimate the effect of attending a charter school in the large urban school district of Milwaukee, which has a long history of charter schools. This study finds that charter schools in this district have no significant overall effect on student achievement. This result is robust to alternative ways of dealing with self-selection, including fixed effect, difference-in-difference propensity score matching and instrumental variables strategies. However, this result masks important heterogeneity in the effectiveness of charter schools across types of charter schools and students they serve.

Further, I estimate the effect of attending the two different types of charter schools: instrumentality and non-instrumentality charter schools. Attending a non-instrumentality charter school has a positive and significant effect on student achievement while attending an instrumentality charter school has a negative and significant effect. I show that students in non-instrumentality charter schools would read at a grade level higher than similar students who attend an instrumentality charter school in two years, and students who attend a traditional public school in three years. This finding is comparable to the study of charter schools in Boston conducted by Angrist et al. (2009).

However, I cannot specifically identify the factors that lead to the difference between these effects. Most of the non-instrumentality charter schools are smaller in size as compared to instrumentality charter schools. Additionally, the student-teacher ratio at a non-instrumentality charter school is smaller than at an instrumentality charter school. The collective bargaining power of the teachers' union may make it difficult for the instrumentality charter schools to expand the number of hours of instruction and the number of teachers hired without seriously affecting their budgets. Further investigation to determine whether the negative impacts for an instrumentality charter school are due to peer effects, resource inadequacies or other reasons would be useful.

What these findings make clear is that the details of charter school policies matter. The charter school laws differ from state to state and these differences may relate to whether charter schools are effective in that state. This may explain the mixed results across states. These findings, though limited, suggest continued inquiry and provide an excellent opportunity for future research to study the relationship between charter school laws and the effectiveness of charter schools.

When the results are broken down by race, white and African-American students make positive gains when they attend a charter school. These students are well served by the introduction of charter schools, and this finding may give hope to charter school advocates. Conversely, Hispanic students do worse than similar students in TPS. Previously low achieving students perform better in a charter school and high achieving students perform worse in a charter school. This result is robust to the type and age of the charter school they attend, across the race and the grade level of the student. These effects are substantial and are more than enough to eliminate the difference in two years. Angrist et al. (2009) and Nicotera et al. (2010) find similar large overall effects in other urban school districts.

Policy makers have suggested that converting traditional public schools to charter schools would help student achievement. This study finds that attending charter schools converted from traditional public schools has a negative effect on student achievement. Thus, simply converting schools to a charter school does not improve student achievement.

Despite the fact that charter schools in MPS have not demonstrated the overall benefits envisioned by the school board, charter schools do expand parental choice, and as the authorizers gain experience, careful design of policies can improve student outcomes.

Specifically, charter authorizers might choose to promote more non-instrumentality charter schools rather than instrumentality charter schools. Equally important is identifying the characteristics of charter schools that are more successful at improving student achievement. This can help authorizers make more informed decisions.

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Appendix A

Table 16: Characteristics of MPS elementary and middle charter schools.

Table 5: MPS Elementary and Middle charter school characteristics															
Sch Name	**Cap.**	**St. Yr**	**Grade**	**Inst**	**Voc**	**DI**	**Sci**	**Mont**	**Risk**	**Bil**	**C.A**	**MPS**	**Priv**	**Tchr**	**Yr**
Highland	200	1996	K-8					Y					Y		
Fritsche	1030	1999	6-8	Y						Y		Y			
WI Career	350	2000	6-12				Y				Y				
Bruce	740	2000	K-8							Y			Y		
Westside	750	2000	K-8	Y			Y					Y			
MLTC	120	2001	5-8		Y				Y						
Audubon	860	2001	6-8	Y		Y	Y		Y			Y			
Whittier	200	2001	K-5	Y								Y		Y	
Fairview	583	2001	K-8	Y								Y			
IDEAL	200	2001	K-8	Y										Y	
Wings Ac.	150	2002	1-12						Y		Y				Y
Northern Star	40	2002	6-9	Y					Y					Y	Y
Carter	280	2003	K-5										Y		Y
LaCausa	500	2003	K-8							Y			Y		
Prep School	100	2004	6-11												
ALBA	225	2004	K-5	Y						Y	Y			Y	
HAPA	375	2004	K-8							Y					
Humboldt	578	2004	K-8	Y		Y	Y			Y		Y			
Honey Creek	360	2005	K-5	Y		Y						Y			
Kosciuszko	500	2006	K-8	Y				Y		Y		Y			
MACL	413	2007	K-8	Y		Y				Y					
Malcolm X *	536	2003	6-9	Y					Y						
Siefert *	342	2002	K-5	Y								Y			
Walker Inter. *	793	1999	6-9	Y					Y	Y					
New hope *	-	2003	6-12				Y		Y					Y	
Total Num		25		15	1	4	5	2	7	9	3	9	4	5	3

*Inst stands for Instrumentality charter schools. Voc stands for Vocational/School-to-work schools. DI stands for Direct Instruction method of teaching. Sci stands for Science and Technology schools. Mont stands for Montessori schools. Risk stands for At-risk schools. Bil stands for Bilingual schools. C.A. stands for creative arts. MPS stands for previous MPS public school. Priv stands for previously private school. Tchr stands for teacher led and lastly Yr stands for year around schools. *- Indicates that these schools were closed.*

Appendix B

Propensity Score Matching model explanation

In an experimental setting where assignment to treatment is randomized, the treatment and control groups are drawn from the same population. The average treatment effect is $\alpha = E[(Y^1_{igt} - Y^1_{i(g-1)(t-1)}) - (Y^0_{igt} - Y^0_{i(g-1)(t-1)})]$, which is readily estimated. In the case of estimating the effect of attending a charter school, since students are not randomly assigned to the treatment and control groups (self-selection issue), the effect may be biased. The mean effect of attending a charter school on its students (average treatment of the treated) is,

$$\alpha = E[(Y^1_{igt} - Y^1_{i(g-1)(t-1)}) - (Y^0_{igt} - Y^0_{i(g-1)(t-1)})|CH_{igt} = 1] \tag{7}$$

$$= E[(Y^1_{igt} - Y^1_{i(g-1)(t-1)})|D = 1] - E[(Y^0_{igt} - Y^0_{i(g-1)(t-1)})|CH_{igt} = 1] \tag{8}$$

This equation cannot be estimated directly, because $(Y^0_{igt} - Y^0_{i(g-1)(t-1)})$ is not observed for the treated units. Assuming selection on observable covariates, namely, $Y^1, Y^0 \perp CH|X$. With this assumption, there is no systematic pretreatment difference between the two groups, conditional on the observable covariates, X. This allows to identify the effect of attending a charter school,

$$\alpha = E[(Y^1_{igt} - Y^1_{i(g-1)(t-1)})|D = 1] - E_{X|D=1}[(Y^0_{igt} - Y^0_{i(g-1)(t-1)})|D = 1, X] \tag{9}$$

$$= E[(Y^1_{igt} - Y^1_{i(g-1)(t-1)})|D = 1] - E_{X|D=1}[(Y^0_{igt} - Y^0_{i(g-1)(t-1)})|D = 0, X] \tag{10}$$

The problem with this matching strategy is that the estimation becomes difficult, if the number of observable covariates are high. Rosenbaum and Rubin (1983) show that if the outcome is independent of the treatment conditional on X then the outcome is also random, conditional on probability to attend a charter school, $p(X) = Pr(CH_{igt} = 1|X)$. Thus a multi-dimensional matching problem can be converted to a single dimensional problem. The above equation is then also valid for $p(X)$. The estimate for the effect of attending a charter school can be estimated using the following equation:

$$\alpha = E[(Y^1_{igt} - Y^1_{i(g-1)(t-1)})|CH_{igt} = 1] - E_{p(X)|CH_{igt}=1}[(Y^0_{igt} - Y^0_{i(g-1)(t-1)})|CH_{igt} = 0, p(X)] \tag{11}$$

Appendix C

Logistic Regression Results of the Propensity Score Estimation

Table 17 shows the results of the propensity score estimation. The model includes grade and year dummies along with student demographics and distance from the closest charter school and TPS. A dummy variable which takes a value of 1 when a charter school is closer than a TPS (Closest is charter), is also included. Students who live further from a charter school are less likely to attend one. Similarly, an increase in the distance from the closest TPS increases the possibility of attending a charter school.

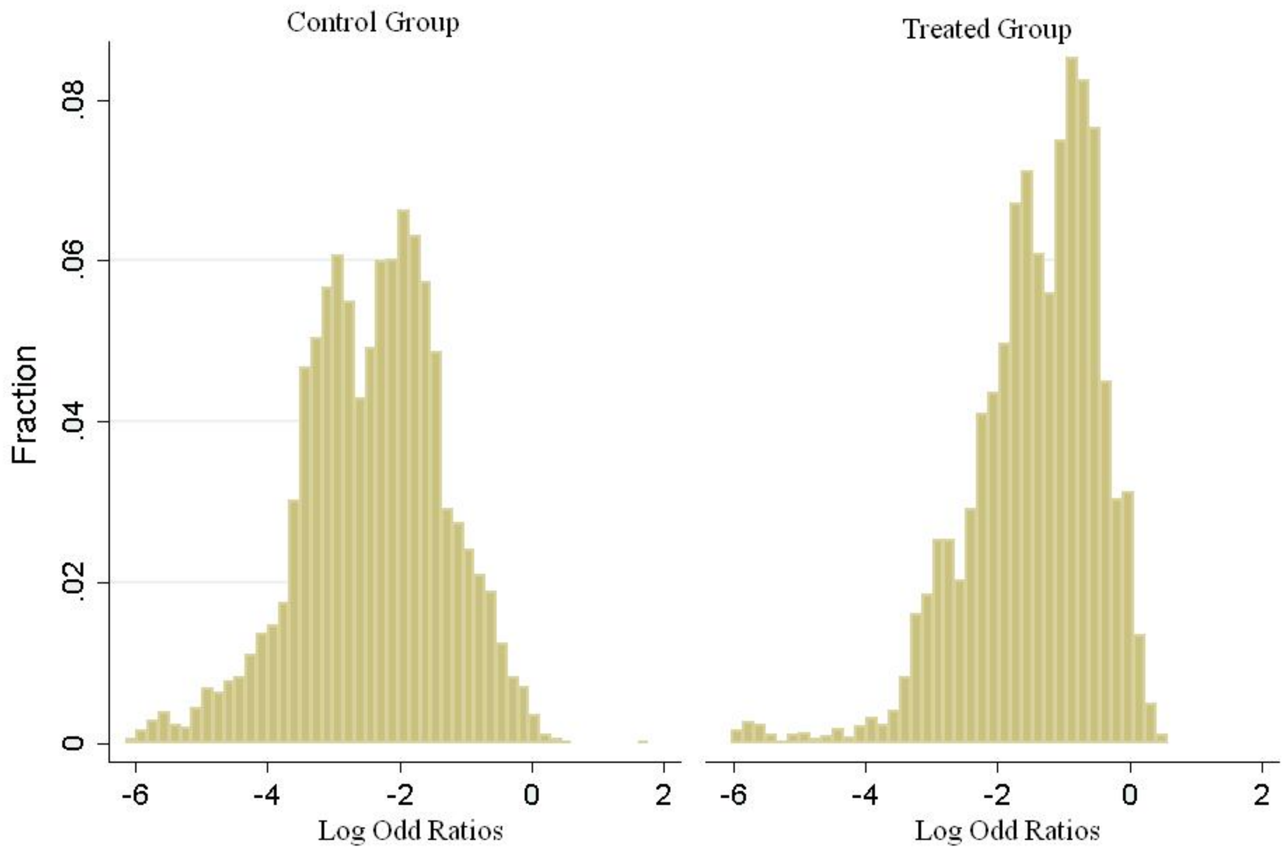
Table 17: Factors affecting attending a charter school obtained from the logistic regression

	Coefficient	Std. Err.
Charter distance	-0.90***	0.142
$(Charter\ distance)^2$	0.08**	0.040
TPS distance	0.63**	0.297
$(TPS\ distance)^2$	-0.09**	0.045
Closest = Charter	0.16	0.124
Previous test	0.01	0.084
Mobility	-0.06	0.269
Female	-0.04	0.046
F/R Lunch status	-0.08	0.131
ELL status	-0.39	0.290
Sp Ed. Status	-0.05	0.075
Asian	1.63**	0.653
Hispanic	1.20**	0.513
White	1.20**	0.442
Number of Obs	72,847	
Number of schools	165	
$Psuedo\ R^2$	0.13	

-significant at 10% **-significant at 5% *- significant at 1%. Reference category for race is African-American. Reference category for special education is not in special education. Reference category for ELL is advanced level. Reference category for Free and Reduced Lunch is No Free Lunch status. Charter distance is the minimum distance of a charter school from the students residence. TPS distance is the minimum distance of a TPS from the students residence. Closest is charter is a dummy which takes a value of 1 if the closest school to the student is a charter school.*

Appendix D

Figure 1: Odds ratio of propensity score for treated and control groups



Appendix E

Table 18: Covariance balance test for propensity score matching

Variable	Sample	$\overline{X}_{Treated}$	$\overline{X}_{Control}$	%bias	% Reduction in bias	t-stat	p-value
Charter distance	Unmatched	0.783	1.335	-44.9		-39.72	0.00
	Matched	0.770	0.786	-1.3	97%	-1.12	0.26
$(Charter\ distance)^2$	Unmatched	2.024	3.383	-7.7		-10.01	0.00
	Matched	1.664	1.501	0.9	88%	0.8	0.42
TPS distance	Unmatched	0.352	0.323	4.7		5.88	0.00
	Matched	0.340	0.331	1.6	66%	1.27	0.21
$(TPS\ distance)^2$	Unmatched	0.766	0.241	4.3		6.12	0.00
	Matched	0.507	0.286	1.8	58%	1.57	0.12
Closer	Unmatched	0.257	0.121	35.4		36.04	0.00
	Matched	0.257	0.261	-1	97%	-0.6	0.55
Prev test	Unmatched	0.155	0.036	12.5		11.15	0.00
	Matched	0.155	0.162	-0.7	94%	-0.48	0.63
Mobility	Unmatched	0.183	0.250	-16.4		-14.28	0.00
	Matched	0.183	0.184	-0.4	98%	-0.28	0.78
Female	Unmatched	0.491	0.496	-1.1		-0.99	0.32
	Matched	0.491	0.490	0.2	82%	0.1	0.92
F/R Lunch status	Unmatched	0.742	0.794	-12.2		-11.42	0.00
	Matched	0.743	0.743	-0.1	99%	-0.06	0.95
ELL status	Unmatched	0.118	0.083	11.7		11.27	0.00
	Matched	0.118	0.117	0.5	96%	0.31	0.76
Sp. Ed. Status	Unmatched	0.139	0.170	-8.6		-7.56	0.00
	Matched	0.139	0.140	-0.1	99%	-0.06	0.95
African-American	Unmatched	0.288	0.611	-68.6		-60.46	0.00
	Matched	0.288	0.284	1	99%	0.74	0.46
Asian	Unmatched	0.087	0.041	19		19.83	0.00
	Matched	0.087	0.092	-2.2	88%	-1.3	0.19
Hispanic	Unmatched	0.376	0.192	41.6		40.86	0.00
	Matched	0.376	0.375	0.1	100%	0.05	0.96
White	Unmatched	0.214	0.116	26.6		26.52	0.00
	Matched	0.214	0.215	-0.3	99%	-0.2	0.85

Appendix F

Robustness Check of Instrumental Variable Approach

If the first stage of an instrumental variable approach is a probit then the predicted probability, $\widehat{Pr(CH_{igt} = 1)}$, is non-linear in X_{igt}. Substituting $\widehat{Pr(CH_{igt} = 1)}$ instead of CH_{igt} yields the following second stage equation.

$$Y_{igt} - Y_{i(g-1)(t-1)} = \alpha \widehat{Pr(CH_{igt} = 1)} + \beta' X_{igt} + \varsigma_{igt} \tag{12}$$

The above equation can be estimated without an exclusion restriction but the results of this model depends solely on the functional form of the probit, thus most researchers are skeptical of these results. This approach, where the estimation is done without an exclusion restriction as shown in equation (12), gives similar estimates as in Table 15 but with slightly larger standard errors, as expected.

Next, Altonji, Elder and Taber (2005b) show that if the probability of attending a charter school is used as an instrument, then the identification can come from the nonlinearity of the probit instead of the variations in Z_{igt}. I test this using the following method they propose,

$$Y_{igt} - Y_{i(g-1)(t-1)} = \alpha_1 \widehat{Pr(CH_{igt} = 1)} + \alpha_2 \Phi(\widehat{\delta' \overline{Z_{gt}} + \beta'} X_{igt}) + \beta' X_{igt} + \varsigma_{igt} \tag{13}$$

The second term on the right hand side captures the nonlinearity part of the probit. The estimated coefficient α_1 measures the extent to which the variation in excluded instruments are influencing attendance of a charter school. The results show that the identification comes from the instrument.[15]

[15] The results of this estimation can be obtained from the author upon request.