Undergraduate Economic Review

Volume 9 | Issue 1 Article 11

2012

An Empirical Assessment of the Performance and Competitive Effects of Los Angeles County Charter Schools

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Abstract

This paper evaluates the performance of charter elementary schools in Los Angeles County in three ways. First, I compare charter school performance to public school performance, controlling for a number of key characteristics. Second, I study the characteristics that appear to influence charter school success as compared to public school success. Third, I study the "competitive effect" of charter schools, examining how geographical proximity to charter schools affects the performance of traditional public schools. I find evidence that, ceteris paribus, traditional public schools score higher than charter schools, except in majority African American schools. Further, I find that the opening of charter schools affects nearby traditional public schools negatively.

Keywords

Competitive, Charter, Schools, GIS, Scores

Cover Page Footnote

Thanks to everyone who has helped me in the process of writing this paper. Specifically, I would like to thank Warren Roberts for helping me use GIS to gather data, Pierangelo de Pace for econometric assistance, Gary Smith and Jack Lewis for their edits and comments, and Fernando Lozano for helpful discussion.

Introduction

One of the rallying calls of proponents of “school choice” reforms is that introducing competition into the school system will improve the effectiveness of teachers and principals, and enhance overall student achievement. Central to the school choice movement is the advent of charter schools, schools funded publicly but operated largely privately. Charter school legislation was first passed in 1991. Since then over 4700 charter schools have been introduced in 40 states (CREDO, 2009). In addition, President Obama has made charter schools one of the focal points of his education agenda.

The growth of charter schools has fueled a national debate about the advantages and disadvantages of a more market-based public school system. Advocates of the charter school movement argue that charter schools not only provide attendees with a higher quality education, but also spur nearby traditional public schools (TPS) to higher performance through a competitive effect. Opponents argue that charter schools undermine the goals and ideals of public education, and do not perform better than traditional public schools. I use data from Los Angeles County elementary schools to test empirically 1) whether charter schools indeed outperform traditional public schools, 2) what sorts of elementary charter schools have been most successful in L.A., and 3) whether the introduction of charter schools causes nearby traditional public schools to perform better (what I call the competitive effect).

Background

Charter schools receive public funding, but are not subject to all the regulations imposed on traditional public schools. They remain accountable, though, to their local school board or state sponsoring agency, with low performance often leading to closure. High-demand, oversubscribed charter schools admit students based on a lottery system, not on previous grades or test scores. In 26 states and Washington, DC, the number of charter schools that can exist at any point is capped, which can lead to oversubscription and long charter school wait lists (National Alliance for Public Charter Schools, 2009). Charter schools, on average, receive less funding per pupil than similar public schools; however, they often do not enroll as many students requiring special education or support services. A 2008 study on charter school funding in 40 states and Washington, DC found charter school funding to average just $6,585 per student annually, compared with $10,771 at TPSs (Center for Education Reform, 2008).

California passed legislation allowing for the introduction of charter schools in 1992, preceded only by Minnesota. Since then, California has become home to more charter schools than any other state. Original legislation in the Charter Schools Act restricted the number of charters in California to 100. This cap was later amended in 1998 to allow an additional 100 charter schools each year. As of 2006, 1 out of 20 public schools in California was a charter school, and 1 out of 50 students attended charter schools (American Institutes for Research, 2006). California’s charter schools are concentrated in urban areas, with LAUSD (Los Angeles Unified School District) by far the most charter-friendly district in the state. Los Angeles County has in total over 270 charter schools (California Department of Education, 2012).

Charter schools are established by business-people, parents, or other community members interested in starting and running a school. In order to open a school in California, founders must present their ideas and strategies to the governing board of their home school district. If the petition is approved on a local level, the proposal is then submitted to the State Department of Education. At this point, the petitioners apply for an implementation grant. If approved, the school is funded by the state, with the amount of funding generally based on average attendance (proposed attendance in a school's first year). After the expiration of the first five-year term, the school must be reapproved by the school board in order to retain funding (Wok, 2012).

If a charter school's initial petition is denied, the founders can try to improve their petition and reapply, or they can appeal to the County Office of Education. According to a representative of the California Department of Education (CDE), petitions are judged based on their satisfaction of legal requirements, their comprehensiveness, and the capability of the people making the petition (Wok, 2012). According to the CDE representative, the biggest hurdle in general for potential charter schools is finding a suitable facility.

Literature Review

There is not a consensus in the existing literature on whether charter schools outperform traditional public schools. There is also not a consensus on whether charter schools exert a positive competitive effect. Further, there has yet to be published a study specifically of Los Angeles schools, although several studies have investigated the whole of California's charter schools. The most comprehensive, up-to-date study of charter school effectiveness is a 2009 study by the Stanford Center for Research on Educational Outcomes (CREDO, 2009). The study, using data from 16 states as well as Washington D.C., did not find charter schools to consistently outperform or under-perform traditional public schools. In five states, charter schools statistically significantly outperformed TPSs, while in six states TPSs outperformed charter schools. In the remaining states results were inconclusive. Some other interesting findings were that elementary and middle school charters on average performed better (compared to traditional public school counterparts) than charter high schools. Further, charter schools were found to be more effective for students who had spent several years at the school already.

In California specifically, a 2005 RAND study found students in start-up charters to outperform comparable traditional public school students (Zimmer, 2005). However, conversion charters (charters converted from TPSs vs. opened independently) did not outperform traditional public schools. Further, charter schools with some independent study or distance-learning component performed worse than traditional public schools. The study also found no measurable competitive effect when looking at the whole of California's charter schools.

Studies comparing charter school and traditional public school performance generally use OLS models. One potential issue with such studies is that students will self-select into charter schools or traditional public schools, introducing the problem of omitted variable bias. To correct for this problem, analyses generally control for student body indicators such as race, percentage of students on free or reduced lunch programs, and student-teacher ratio. Studies have shown that, in California, charter schools do not generally "skim" high-performing students from traditional public schools (American Institutes for Research, 2006). On the contrary, charter school students are generally lower-performing, due partly to the fact that charter schools are often in poorer, urban areas. If student level data are available, researchers often also use student fixed-effects, through which they can track individual students, in order to neutralize this source of selection bias.

There is only a small body of literature assessing the charter school competitive effect. Hoxby (2003) provided the first major study of competitive charter school effects, focusing specifically on charter schools in Michigan and Arizona. She finds charter school introduction to have a positive, statistically significant competitive effect on nearby traditional public schools. Bettinger (2005) also tests Michigan charters, using an instrumental variable to control for school placement, and fails to find a robust competitive effect. Bifulco and Ladd (2006), looking at North Carolina charters, also fail to find a robust competitive effect. However, Booker et al (2006) and Sass (2006) find a small, positive competitive effect in Texas and Florida, respectively. Buddin and Zimmer (2010) fail to find a competitive effect of charter school introduction in California. Buddin and Zimmer also use interviews with TPS principals to add qualitative depth to their study. They find that principals, in general, feel little competitive pressure from the opening of charter schools. Most recently, Imberman (2011) finds that charter school openings have a negative effect on TPS performance at the elementary level, but a positive competitive effect at the middle and high school level.

The main econometric issue one encounters in studying the competitive effect is endogeneity associated with time and location of charter school openings. The problem, in theory, is that the location of charter schools is not randomly determined; rather, charter schools locate (temporally and spatially) in areas where schools are doing poorly. If charter schools aim to substitute for public schools where public schools are not doing a satisfactory job, then charter schools will generally open in areas with low TPS performance. According to this theory, any analysis of competitive effects failing to account for endogeneity of school location would likely find charter school openings to be correlated with low TPS performance.

The competitive effects studies in general use a difference-in-difference approach to reduce the issue of endogeneity in estimating the competitive effect. Another method to control for endogeneity is to instrument for charter school opening. Bettinger (2005) and Imberman (2011) employ this technique, with Bettinger using the instrumental variable (IV) of proximity to a university, and Imberman using an IV based on property available in a specific area. Bettinger and Imberman select variables (proximity to a university and number of properties near a TPS with between 20,000 and 100,000 square feet of building space respectively) that they argue are correlated with the opening of a charter school, and correlated with performance of nearby public schools only through the mechanism of charter openings (the exclusion restriction). In the first stage of the 2SLS regression, they estimate the opening of charter schools based on their respective instrumental variables. In the second stage, they estimate the impact of the opening of charter schools on TPS performance, using results from the first stage as right hand side variables. This technique accounts for endogeneity, and gives an unbiased estimate of the impact of charter schools on nearby TPSs.

Due to difficulty in finding a suitable IV, this study resolves the endogeneity issue by both measuring changes in TPS performance (as opposed to levels) as the dependent variable, and also by controlling for past performance of TPSs. Given that any endogeneity due to past changes in API performance is captured by lags, this study should not suffer from bias due to endogeneity.

School Choice and Competitive Effects Theories

This study tests two theories: first, that charters achieve higher levels of performance than TPSs, and second, that the introduction of charter schools results in better outcomes for nearby traditional public schools. In this section, I further explore the economic roots of the theories, and explore a few reasons why they may not actually apply to charter school implementation in the U.S.

The notion that charter schools should perform better than traditional public schools stems from the idea that markets promote efficiency. While charter schools in California are subject to many of the same rules and regulations as traditional public schools, they also have more scope to operate independently. Charter schools are less subject to inefficiencies posed by the teachers' union, are less restricted in terms of curriculum, and are able to experiment with innovative methods like extending the school day (American Institutes for Research, 2006). Despite these factors, the existing literature does not support the hypothesis that charter schools consistently outperform traditional public schools. This may be due to low levels of information for "choosers" (parents), student composition bias, lower funding levels, or simply the fact that choice does not always promote better outcomes.

The theory that charter school openings should impact TPSs positively views schools and families, at least in part, as rational, utility-maximizing actors. Most basically, parents try to maximize the educational gains for their children through school selection, and schools aim to maintain the public funding that will allow them to remain open.

With the above assumptions in place, one can model the performance of public schools as a function of, among other variables, the competition that they face for public funding. If "funding follows the student," one can then equate competition for public funding with competition for students (Hoxby, 2003). In this model, enhancing the level of competition for students in a certain district by introducing charter schools should spur public schools to improve their performance.

However, there are several reasons to think that the "school competition" model does not aptly describe public school dynamics in the U.S. For one, the argument has been made that teachers do not need externally imposed incentives because of an intrinsic drive to educate students. Further, they are already held accountable through "standards based education reform," a key attribute of NCLB in which public schools are held accountable for providing students with a certain level of proficiency as measured by standardized testing. While these sources of motivation may be enough for some teachers, it is likely that some teachers do respond to external, economic incentives. Additionally, even teachers who are largely self-motivated are not immune to external incentives.

Second, researchers must also take into account the level of the incentives at play. If a principal at a traditional public school feels competition from a nearby charter, the question remains whether he/she will be able to marshal meaningful incentives to relay the competitive effect to teachers, whose actions are ultimately responsible, to a large degree, for student learning.

Third, a competitive effect will only take hold in a policy environment where the “money follows the student” (Hoxby, 2003). If failing schools lose students to charter schools, but are then provided additional funding in order to fix their deficiencies, teachers at the failing schools will not have any incentive to improve. In California, however, while the school funding scheme is quite complex, money is generally awarded to schools on a per-student basis (Bersin, 2008). While this sort of system may promote a competitive effect, it may not be observed in the data. If schools that lose students to charter schools also lose funding, the loss of funding will likely impact performance negatively, possibly negating any competitive effect.

On the demand side, further reason to question the competitive effects theory is that parents often do not have full information on the quality of schools in their district. Even if they do, studies have shown that they frequently fail to respond to failing schools by seeking alternatives like charter schools (CREDO, 2009). One reason may be that, outside of the big names like KIPP, charter schools have not been shown to consistently outperform traditional public schools. Further, issues of convenience, friends, and uncertainty add additional costs to parents sending their child to a new school. In other words, for parents to have their children switch schools, the new school must exceed the old school in quality by more than the cost of the change.

Despite the myriad doubts, the “school competition” theory remains compelling, and is worth testing empirically due to the implications of the results for the charter school movement.

Data

This study uses yearly API scores from the CDE for Los Angeles County TPSs and charter schools from 1998 through 2009, as well as CDE data on other school-level variables such as percent of students on free or reduced lunch programs, student-teacher ratio, and percentage minority. I selected 1998 to 2009 based on data availability, as well as the fact that a large number of charter schools have opened over that period. The data set contains a total of 11258 API score observations amongst 1208 LA County public and charter schools.

The API is a single number, from 200 to 1000, reflecting a school’s performance on statewide assessments in a number of academic areas. It was instituted as the cornerstone of California’s 1999 Public Schools Accountability Act. The API score relies heavily on standardize testing, primarily the CST and CAHSEE. However, it also takes into account factors like attendance and graduation rates. Certain funding awards and incentives are based on API improvement (CDE).

To construct the “charter competition” variables, I use Geographical Information Systems (GIS) software to geo-code addresses from the CDE website for elementary TPSs and charter schools. Geo-coding software takes the addresses and places them on a map in the GIS program. I first create a 5-mile buffer around each public school, and create a variable indicating the number of charter schools within the buffer. I then determine the closest charter school to each TPS, and record the distance as the crow flies.

I also conducted two interviews. In the first, I talked with a CDE representative about the process for starting a charter school. In the second, I talked with a teacher at a traditional public school about competition from charter schools.

Models and Results

Part 1: Comparing Charter and TPS performance

In Part 1 of this study, I compare elementary charter school and TPS API score performance from 1998 through 2009. Los Angeles County contains 84 elementary charter schools, compared to 1224 elementary traditional public schools. Table 1 shows several summary statistics with respect to these schools. Mean API score for charter schools over the period was 788.92, with a low of 410.8 and a high of 910.6. Charter schools, on average, sustained an annual increase of 14.5 API points, or 3.7 percentage points. Charter schools tended to be substantially smaller than TPSs, with fewer students on free or reduced lunches, fewer minority students, and smaller class sizes.

For traditional public schools, mean API score over the period was 719.92, with a low of 311 and a high of 988. API score on average rose by 1.92 percentage points over the period.

Figures 1 and 2 show no significantly disruptive outliers in API scores. The Charter and TPS API distribution shown have a rightward skewness, reflecting more variation in scores at the lower end of the distribution than at the upper end.

The base API regression for school *i* in year *t* is:

$$API_{it}=\beta_1+ \beta_2 Charter_i+ \beta_3' X_{it}+ \delta_t+ \varepsilon_{it} \qquad (1)$$

Charter is a dummy variable indicating charter status, while X_{it} indicates a vector of control variables, and δ_τ is a vector of year fixed effects. The control variables in the basic regression include total enrollment, percentage of students on free or reduced meals, percent of students from minority backgrounds, average pupils per teacher, average class sizes, and a set of dummy variables for the most highly represented ethnic group at the school.

I do not use lagged API on the right hand side because a Woodridge test for autocorrelation indicates serial autocorrelation of error terms to be an issue, even when including up to five lagged values of API. Keeping lagged API terms on the right hand side would thus cause estimation bias.

While inspection of residuals does not immediately indicate heteroskedasticity, a Breusch-Pagan test on the residuals of the base regression indicates that error terms are heteroskedastic (chi-squared=104.21, p<.0001). I also need to account for the serial correlation discussed above. Further, I adjust standard errors based on district clustering. The standard errors I use are clustered and robust to serial correlation and heteroskedasticity. The results of the base regression can be viewed in Table 2.

Despite the fact that charter schools, on average, have higher API scores than TPSs, the charter dummy shows up negative in the basic regression, with a coefficient of -6.96. This result is not significant, though. The negative result is related to the control variables. Charter schools, on average, have lower total enrollment, lower percentage of students on free or reduced school lunches, and lower percentage of minority students than traditional public schools. All three of these variables carry statistically significant negative coefficients in the base regression. Thus, if charter schools had the same general characteristics as TPSs, the model suggests they would score worse on the API. The R squared for the base regression is .76, indicating that the chosen variables explain a good deal of the variation in API scores. Consistent with previous studies, percentage minority and percentage of students on free meals are negative predictors of API score, while majority Asian is the strongest positive predictor of API score.

The results of the base regression are robust to transformations of the dependent variable (API scores). I first use a log transformation of API (Column 2), which yields a coefficient of -.0143 on the charter dummy, also insignificant at the 5% level. Second, I use the change in API scores (Column 3) from one year to the next as the dependent variable. With differences in API scores as the dependent variable, using four lagged differences in API on the left hand side neutralizes serial correlation in the error term. I thus include these terms in the regression, and also include one lagged API level term to control for regression to the mean. This transformation yields a coefficient on the charter dummy of -10.32, indicating that a school's charter status results in a reduction in improvement of over 10 points each year. Finally, I use percent change in API as the dependent variable (Column 4), once again including four lagged values of the dependent variable on the left hand side. The coefficient on charter status of -.649 is not statistically significant.

In a second modification to the base regression, I introduce interaction variables between the charter dummy and important control variables like pupils per teacher and percentage of students on free or reduced meals. Introducing interactions controls not only for characteristics of each school, but also for the impact of certain characteristics when they are observed in charter schools. For example, the coefficient on the interaction variable between minority and charter gives the impact on test scores of *percent minority* specifically in charter schools. The regressions with interaction terms included can be viewed in Table 3.

Including the interaction term in the model results in a substantial increase in the magnitude of the negative charter coefficient. The coefficient on *charter* becomes significantly different from 0 at the 5% level. Coefficients are similarly larger with transformations of API levels as dependent variables.

Interestingly, both the interaction between charter and majority black, the interaction between charter and majority white, and the interaction between charter and percentage minority turn out statistically significant and positive. This indicates that, while charter status generally results in lower performance, the effect is mitigated if a school is majority black, majority white, or has a high percentage of minority students. Charter status has a highly negative impact (controlling for important characteristics) for majority-Hispanic schools, which encompass 40% of LA County's charter schools.

There are several potential challenges to these results. The largest is that, due to lack of student-level data, I am not able to track the movement of students from TPSs to charter schools. In other words, I am not able to control for characteristics of students outside of the control variables on the general characteristics of the schools. It could be the case that there are unobservable characteristics of students who choose to go to charter schools that are driving the results. If we think that charter school students tend to have positive "unobservables," then the charter school dummy should be even more negative. If we think charter school students have negative "unobservables," this might explain the negative coefficient on the charter dummy.

Studies in California have shown, though, that charter schools do not seem to skim higher-performing students from TPSs; rather, they seem to take on low-performing students. (Buddin, 2006) This may be due to the fact that charter schools locate in poorer, urban areas, where sudents are generally lower-performing on standardized tests. If this is the case, the included controls should account for this effect. It could be though, that other negative "unobservables" are driving the lower performance of charter schools, which would call into question the findings of this study. Further student-level research is necessary to determine whether this is indeed the case.

Part 2: Focusing on Charter School Performance

In Part 2 of this study, I focus specifically on charter school performance, examining how charter schools differ from TPSs in terms of the factors that impact API performance.

In order to test empirically the differences between charter school and TPS factors that lead to API success, I run the base regression (Equation 1) first on the sample of charter schools, and then on the set of observations encompassing only TPSs. Then, I compare the coefficients from each regression, looking for significant differences. The results of these regressions are in Table 4.

There are several coefficients that vary dependent on whether one looks at charter or traditional public schools. Most striking is that amongst TPSs, the dummy variable "black" is strongly negative (in both levels and % change), while in the charter set the dummy variable shows up positive, although only weakly significant (10% level) due to the small sample size. This is an interesting result, indicating that majority black schools, on average, do far better if they are charter schools. *Percentage minority* also has a statistically significant negative coefficient for TPSs, but a small positive coefficient for charter schools. This indicates that, ceteris paribus, higher-minority schools will tend to do better if they are chartered. While other coefficients, such as number of teachers and pupils per teacher, vary as well, their variation is not statistically significant.

The descriptive statistics support the regression results that majority black schools perform better if they are chartered. Table 5 shows that mean API for majority-black TPSs over the period was just 663.72, but for majority-black charter schools was 757.01, an increase of over 14%. While majority-white and majority-Hispanic schools also performed better if they were chartered, the gains were not nearly as great as for majority-Black, and can be attributed (based on previous regression results) to other school and student composition characteristics.

Aside from school ethnic makeup, I am also interested in how the performance of charter schools varies depending on two charter-specific variables: first, when the charter school was opened, and second, whether the charter school is a startup or conversion.

Startup charters are charter schools opened in a new location. Conversion charters, on the other hand, are charter schools that were converted from TPSs or private schools. Around 60% of the charter elementary schools in LA County are startups, compared to 40% conversion.

Charter schools in LA County are more likely to have been opened in recent years, as Figure 3 demonstrates. A high number were opened shortly after charter legislation in 1992, followed by a stretch of fewer openings lasting until around 2003. From 2003 to 2010, a large number of charters were opened in each year.

In order to test the impact of number of years in existence and type, I restrict the sample to charter schools, and run the base regression including the two new variables (years_existed and type).

$$API_{it}=\beta_1+ \beta_2 Years\_existed + \beta_3 Type + \beta_4 Lagged\_API_{it}+ \beta_5 ' X_{it}+ \delta_t+ \varepsilon_{it} \quad (2)$$

The results of this regression are reported in Table 6.

Judging by API levels, the number of years a charter school has existed (calculated as 2012 minus the year the school was founded) positively affects performance. While the coefficient of 1.4 is small, it is significant at the 5% level. It indicates that, ceteris paribus, each year a charter school has existed will raise its API score by 1.4 points. It makes intuitive sense that a charter school will improve as it becomes more entrenched in a community. Further, the fact that a charter school has not been closed after the five-year trial period indicates decent performance.

The coefficient on the dummy variable *startup*, on the other hand is strongly negative. The coefficient on the variable startup indicates that ceteris paribus, a school being a startup vs. a conversion charter decreases API score by around 71 points, and decreases average yearly improvement by 7.7 percentage points. However, the result is only significant with API levels as the dependent variable, and at the 10% level (due to small sample size). This result indicates that the existing infrastructure that comes with being a conversion charter school is beneficial to the school's performance. It also runs contrary to the findings of Buddin (2006).

The most important challenge for these results is, once again, the possibility of omitted variable bias. It could be the case that the *black* variable for charter schools reflects some characteristic of black students who attend charter schools that is not captured by other control variables. For the data on startup vs. conversion, it is also possible that there is some unobserved aspect of startup charter schools, such as bias in geographical location, that leads to persistently lower API scores. That being said, the results are quite convincing that charter schools are 1) better at educating black students than TPSs, 2) generally do better when they are converted from traditional public schools versus started up independently, and 3) improve with age.

Part 3: The Competitive Effect

In Part 3 of this study, I examine whether the geographic proximity of charter schools has an impact on the performance of traditional public schools. To do so, I generate several geography-related variables from GIS: 1) the name of the nearest charter to each traditional public school, 2) the distance (in feet, as the crow flies) to that charter and 3) the number of charters in a 5-mile radius from each TPS. Figure 4 shows the location of all elementary charter and TPSs in LA County. I also control for the distance to the nearest private elementary school and the number of private elementary schools in a 5-mile radius. These variables are meant to account for any competitive effect stemming from private schools. Table 7 lists elementary charter schools in LA county, and also gives the number of public schools for which they are set as the nearest charter school.

The mean distance to the nearest charter school for a TPS is 38,770 ft, with a minimum of 30 feet and a maximum of over 2 million feet. There are an average of 6 charter schools within a 5-mile radius of each TPS, with a minimum of 0 and a maximum of 44. Both *distance to* and *number of* charter schools' distributions are skewed to the left, with long tails to the right (figures 5 and 6).

In order to test the impact of geographical proximity to charter schools on TPS performance, I create variables reflecting characteristics of the nearest charter school. First, I look at when the nearest charter school was opened. I create a dummy variable called *year_of*, which registers as a 1 if the API being reported is in the year that the nearest charter school was opened and a 0 otherwise. I continue creating a set of dummy variables for each year following or preceding the opening of the nearest charter school. These variables indicate the impact on API scores for being in the year "x" years before or after the opening of a charter school nearby.

I run the base regression, except in this model I use percent changes in API as the dependent variable, restrict the sample to TPSs, and include the discussed geographic proximity variables. I only use differences (in percentage terms) here to reduce issues of endogeneity, which I will discuss in a subsequent section. Due to lack of serial correlation issues with the differenced variable on the left hand side, I am able to control for lagged values. The following represents the model I test in this section.

$$\%\Delta API_{it} = \beta_1 + \beta_2 count + \beta_3 distance\_charter + \beta_4' year\_open + \beta_5' Lagged\_\%\Delta API_{it} + \beta_5' X_{it} + \delta_t + \varepsilon_{it} \qquad (3)$$

For each TPS in the sample, *count* gives the number of charter schools within a 5-mile radius, *distance_charter* gives the distance to the nearest charter school, and *year_open* is a vector of dummy variables indicating when the nearest charter school was opened. For example, if *year_of* is coded as a 1 for a given observation, it indicates that the nearest charter school was opened in that year. If the variable *three_years_after* is coded as a 1, it indicates that the observation year is three years after the opening of the nearest charter school. Further, if the variable *three_years_before* is coded as a 1, it indicates that the observation year is three years before the opening of the nearest charter school. This is intended to capture the competitive effect of the opening of the school in subsequent years, as well as the possible competitive effect in the buildup to the opening of the school. The results of this regression are in Table 8. Column 1 indicates the base regression, with Column 2 representing a robustness check.

In the base regression (Column 1), both *distance* and *count* show up statistically significant at the 5% level. The coefficient on *distance* indicates that a greater distance to the nearest charter increases API improvement, suggesting that a charter in close proximity has a negative effect. The coefficient on *count* indicates that each additional charter school within a 5-mile radius reduces charter school API improvement by .05 percentage points. This result suggests that the presence of charter schools in an area hurts the performance of TPSs. In the base regression, the only significant charter opening indicator variables are those representing one, three, and four years after an opening. The coefficients are negative as well, suggesting that charter school openings are negative predictors of future API scores.

Column 2 introduces a robustness check in which I control for several characteristics of the nearest charter school: total enrollment, percentage of students on free or reduced lunches, percentage students who are minorities and API score of the charter school. Due to data limitations, controlling for these variables reduces the sample size. In this model, due to lower sample size, the negative coefficient on the variable for count loses strength, becoming no longer significant at the 5% level. Also, the *distance* variable switches signs, indicating that the effect of distance to the nearest charter schools is not robust. An interesting result with this robustness check is that the coefficient on *year_of* becomes statistically significant and negative, with a coefficient of -2.06, while the coefficient on *four_years_after* loses power, no becoming longer statistically significant. This result indicates that, controlling for charter school characteristics, the opening of a charter school still hurts nearby TPSs, but the effect is stronger in the year of or soon after its opening.

Overall, I find evidence to reject the hypothesis that charter schools exert a positive competitive effect on nearby TPSs. To the contrary, I find that both the presence of charter schools and the opening of new charter schools to be correlated with reductions in TPS API improvement. Further, I find that these negative effects, once one controls for charter school characteristics, are observed most strongly in the year that the charter school opens and the year after. There is also some evidence that these negative effects are observed three to four years after the opening of a charter school.

The two most likely explanations for the negative effect are loss of students and loss of funding, which are actually very much intertwined. While past studies of Los Angeles schools have not found charter schools to “skim” the highest performing students from TPSs (Buddin, 2006), it could be that there are still unobservables at play here. For example, while it has been shown that the highest performing students do not disproportionately leave TPSs for charter schools, it could be that students with high improvement potential disproportionately move from TPSs to charter schools. This sort of bias could result in the observed negative effect—if students with high improvement potential leave TPSs for charters, TPSs will experience lower improvement in years of and after nearby charter school openings.

Second, loss of funding that comes with students leaving for charter schools could negatively impact the performance of TPSs. Los Angeles public schools are funded based on their student populations (Robertson, 2012). While this was previously cited as a reason to think positive competition may take place, it could actually lower TPS performance in years following the opening of nearby charter schools (assuming students transfer from nearby TPSs to that charter). Even if schools have fewer students to educate, loss of funding could force them to cut programs, fire teachers, or take other measures likely to inhibit learning. Thus, the effect of the opening of charter schools could run both directions, both stimulating competition and reducing a school’s resources. These factors do not explain, though, why TPSs do not improve their performance in the years leading up to the opening of a charter school, when they know a charter school will soon exist nearby, but have not yet experienced budget cuts. This result calls into question any sort of positive competitive effect in elementary schools.

There are several potential issues with the presented results. First, the distance variable is not a very precise measure of competitive effect. There are many possible unobservables that could be associated with both closeness of the nearest charter school and API improvement. This may explain why the *distance* variable switches sign based on model specifications.

Second, I do not have data to account for a situation in which a charter school opens near a TPS, and then another charter school opens even closer to the same TPS. In this case, the data do not capture the effect of the first charter school, due to the fact that the GIS program is only capable of finding and recording the nearest charter school. The ability to find and record all instances of charter school openings would add depth to the analysis.

Part 4: Endogeneity Checks and Determinants of Charter Location

In order to confirm that bias of charter school openings is not severely impacting the results, I run auxiliary regressions on the determinants of charter school openings. These tests can also help determine factors that influence the location and timing of charter school openings. I specifically am testing for whether past changes in API scores of TPSs encourage charters to open nearby. I model characteristics indicating charter school proximity to each TPS as a function of the general control variables (from Equation 1), API and percent change API, and their lags going back five years.

$$\text{Charter\_Proximity}_{it} = \beta_1 + \beta_2\text{'API}_{it} + \beta_3\text{'chAPI} + \beta_4\text{'X}_{it} + \delta_t + \varepsilon_{it} \qquad (4)$$

The variables for charter proximity that I test are the number of charter schools within a five mile radius of each TPS, the distance to the nearest charter school, and the indicator variable *year_of* (coded as a 1 for the year the nearest charter school opens). I am interested here in whether the coefficient on percent_change_API for the present year or any lagged years is significant. This would indicate that charter location is endogenous to the trends in API scores, which would challenge the results in the previous section. The results of this test are in Appendix, Table 9.

With the number of charter schools in a 5-mile radius as the dependent variable, several lags of both API and percent change in API are significant and negative. This indicates that poor API scores in the past for TPSs are correlated with a higher number of charter schools in the area. This somewhat calls into question the previous results linking number of charter schools in an area to performance of TPSs. However, controlling for past API changes in that regression should at least partly solve this issue. Further, the relation between number of charters and performance is not the strongest evidence in that section of a negative competitive effect, so the possible endogeneity issues should not affect the conclusions. While several lags of API levels are also significant, this is not of concern due to the fact that I use differenced API scores in the “competitive effects” regression.

Using the distance to the nearest charter school as the dependent variable, there are no key variables that turn out significant, supporting the idea that the distance from a TPS to the nearest charter is exogenously determined.

Finally, I run a probit regression with the dummy variable *year_of* on the left hand side. In this model, only the second lag of percent change API is significant, and is negative. The second lag's negative coefficient indicates that API decline increases the likelihood that a charter school will be opened nearby in the next two years. While this is an interesting result, the fact that charters are generally planned more than two years before opening mitigates concerns of endogeneity. Furthermore, even if this were still a concern, controlling for lagged percent change in API in the competitive effects regression is likely sufficient to resolve the issue.

Conclusion and Policy Recommendation

There are a few main points to take away from this study that are applicable to education policy both in LA and around the country. First, according to this analysis, although charter schools generally test better than traditional public schools, they actually do not fare any better than TPSs once one controls for important variables.

Second, charter schools appear to be strongly preferable to TPSs only in the case that the school is majority-black. In this case, though, they appear to greatly outperform their TPS counterparts. This is not to say that converting all majority-black schools to charters would strongly improve educational outcomes, though. There are certainly other factors contributing to this result beyond the charter-TPS distinction. It is important to further identify why it is that majority black charter schools do particularly well, and try to reproduce those factors in other schools.

Third, individual charter schools tend to perform better if they have existed for a longer period of time. Thus, it could be that, with time to grow and evolve, charter schools might match or surpass TPSs in performance. Additional research should further investigate the link between years in existence and performance in both TPSs and charter schools.

Fourth, conversion charter schools generally score higher on the API than startup charters. This may be due to the fact that conversion charters can be considered to have a "head start" on startup charters, with facilities and students often in place from the beginning. Perhaps school districts should focus more on converting low-performing TPSs to charters than creating entirely new charter schools.

Finally, there is no evidence of a positive competitive effect from charter school openings; rather, the opening of charter schools is correlated with lower TPS performance. I argue that this result is likely due to a combination of loss of funding and loss of students with improvement potential.

Maintaining a competitive school environment in which funding follows the student while not harming failing schools is a challenge for policymakers. I think that funding should continue to follow students. That being said, special attention should be paid to turning around failing schools that lose students. Perhaps some sort of hybrid scheme in which funding continues to follow students, but at a decreasing rate, would be desirable. Further research should better examine how to create a competitive system without overly punishing students and teachers at low-performing schools.

In terms of the possible loss of students with improvement potential, I do not think this is necessarily problematic. Motivated students and families should have the chance to change schools and maximize learning opportunities. Ultimately, mobility in public school education should lead to a more successful system.

The main conclusions from this study support the notion that we must use caution before declaring charter schools to be the solution to America's primary education woes. This paper refutes, at least in the case of Los Angeles County, two claims often made by charter school advocates: first, that charter schools perform better than public schools, and second, that charter school openings induce TPSs to perform better. This does not mean that there is no role for charter schools to play in this country's education reforms. It does mean, though, that we should seek to construct policies that will lead to charter school success while at the same time promoting the improvement of traditional public schools.

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Appendix

Table 1

Column1	Charters	TPSs
API	788.92	719.92
%ΔAPI	3.7	1.92
Enrollment	464.1	688.95
% Free or Reduced Lunches	56%	66.30%
% Minority	71.40%	81.10%
Avg Class Size	20.78	21.9
Pupils per Teacher	22.3	20.2

Table 2: Base regression

VARIABLES	(1) API	(2) logAPI	(3) ΔAPI	(4) %ΔAPI
charter	***-6.958***	***-0.0143***	***-10.32****	***-0.649***
	(8.49)	(0.0106)	(6.071)	(1.077)
% on free meals	-1.47***	-0.002***	-1.3**□	-0.203***
	(0.124)	(0.000162)	(0.117)	(0.0177)
% minority	-.992***	-.00134***	-.791***	-0.100***
	(0.275□	(0.000381)	□0.237)	(0.0378)
Pupils per teacher	0.106	0.000117	0.0100	-0.00735
	(0.174)	(0.000218)	(0.138)	(0.0238)
Number of teachers	0.667	0.000852	0.755	0.127
	(0.809)	(0.00112)	(0.727)	(0.112)
enrollment	-.0685*	-.0001**	-.068**	-0.0109**
	(0.0354)	(4.82e-05)	(0.0334)	(0.00506)
White	4.050	0.000237	6.312	1.657
	(11.76)	(0.0170)	(10.59)	(1.655)
Asian	82.88***	0.105***	72.86***	11.34***
	(7.587)	(0.00946)	(6.995)	(1.039)
Black	-17.4***	-0.0251***	-19.8***	-3.513***
	(2.768)	(0.00386)	(2.670)	(0.413)
Other	67.83***	0.0850***	24.91***	2.225***
	(14.18)	(.015)	(3.65)	(.597)
R-squared	0.760	0.737	0.836	0.818

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All regressions include fixed year effects. Four lagged values of the dependent variable are used in Columns 3 and 4.

Table 3: Base regression with charter interactions

	(1)	(2)	(3)	(4)
VARIABLES	API	logAPI	ΔAPI	%ΔAPI
charter	-172***	-0.239***	-128.0**	-17.65**
	(41.49)	(0.0506)	(48.66)	(8.084)
% on free meals	-1.47***	-.00197***	-1.31***	-0.203***
	(0.129)	(0.000168)	(0.122)	(0.0181)
% minority	-1.05***	-.00142***	-.844***	-0.106**
	(0.311)	(0.00□430)	(0.264)	(0.0420)
Pupils per teacher	0.0780	8.75e-05	-0.0102	-0.0105
	(0.163)	(0.000207)	(0.144)	(0.0247)
Number of teachers	0.673	0.000856	0.768	0.129
	(0.796)	(0.00111)	(0.721)	(0.111)
enrollment	-.0685*	-.0001**	-.0694**	-.0109**
	(0.0350)	(4.77e-05)	(0.0331)	(0.00503)
White	1.444	-0.00348	4.562	1.437
	(12.99)	(0.0188)	(11.51)	(1.814)
Asian	82.47***	0.104***	73.15***	11.34***
	(7.667)	(0.00959)	(7.057)	(1.050)
Black	-23.2***	-0.0332***	-24.4***	-4.395***
	(3.290)	(0.00445)	(3.469)	(0.491)
Other	67.75***	0.0849***	24.77***	2.179***
	(14.39)	(0.0150)	(3.724)	(0.605)
charterblack	51.32***	0.0722***	52.10***	9.680***
	(13.93)	(0.0184)	(16.33)	(3.247)
charterwhite	87.58**	0.126***	51.08	7.770
	(35.51)	(0.0468)	(40.68)	(7.290)
charter% minority	1.315***	0.00180***	1.410***	0.175***
	(0.254)	(0.000341)	(0.304)	(0.0450)
charter% on free meals	0.200	0.000331	-0.492	-0.0396
	(0.405)	(0.000532)	(0.507)	(0.0854)
charter pupils per teacher	0.643	0.000580	0.599	0.0799
	(.85)	(.001)	(.673)	(.117)
R-squared	0.762	0.739	0.838	0.819

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All regressions include fixed year effects. Four lagged values of the dependent variable are used in Columns 3 and 4.

Table 4: Comparing charter vs. TPS

VARIABLES	TPS API	Charter API	TPS %ΔAPI	Charter %ΔAPI
% on free meals	-1.45***	-1.293**	-0.204***	-0.205**
	(0.132)	(0.410)	(0.0184)	(0.0715)
% minority	***-1.08****	***0.152***	***-0.113****	***0.0268***
	(0.295)	(0.277)	(0.0397)	(0.0351)
Pupils per teacher	-0.474	0.555	-0.0928	0.0530
	(0.336)	(0.825)	(0.0580)	(0.105)
Number of teachers	-0.70***	0.0198	-0.091***	0.0965
	(0.151)	(0.474)	(0.0197)	(0.0702)
White	0.524	78.20*	1.253	6.080
	(12.32)	(37.76)	(1.738)	(6.658)
Asian	81.60***		11.31***	
	(7.713)		(1.073)	
Black	***-22.4****	***33.62****	***-4.153****	***3.822***
	(3.330)	(16.35)	(0.506)	(3.497)
Other	68.06***		10.31*	
	(13.83)		(5.441)	
Observations	11,569	338	11,103	303
R-squared	0.768	0.529	0.822	0.671

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All regressions include fixed year effects. Four lagged values of the dependent variable are used in Columns 3 and 4.

Table 5: TPS and Charter API performance by largest ethnic group

Charter Schools		TPS	
Largest Ethnic Group	Mean API	Largest Ethnic Group	Mean API
Black	757.01	Black	663.72
Latino	721.93	Latino	683.70
White	858	White	831.57
		Filipino	857.4
		Asian	849.13

Note: there are no majority Filipino or Asian charter schools

Table 6: Investigating the impact of years in existence and type (startup vs. conversion) on performance.

VARIABLES	(1) API	(2) %ΔAPI
years_existed	***1.405****	***0.0273***
	(0.376)	***(0.0750)***
startup	***-71.04****	***-7.682***
	(35.79)	***(5.450)***
% on free meals	-0.994**	-0.177**
	(0.340)	(0.0606)
% minority	0.476*	0.0503
	(0.222)	(0.0391)
Pupils per teacher	-0.494	-0.0983
	(0.867)	(0.0711)
Number of teachers	-1.73***	-0.0822
	(.294)	(.048)
White	71.29	5.091
	(41.25)	(8.274)
Black	64.14***	9.440**
	(11.49)	(2.753)
R-squared	0.600	0.701

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All regressions include fixed year effects. Four lagged values of the dependent variable are used in Columns 2.

Table 7: List of charter schools in LA County, and how often they appear as the "nearest" to a TPS

Charter	Frequency
Academia Moderna	5
Academia Semillas del Pueblo	7
Accelerated	1
Antelope Valley Learning Academy	1
Ararat Charter	13
Aveson School of Leaders	19
Barack Obama Charter	108
CHIME Institute's Schwarzenegger Commun	9
CLAS Affirmation	4
Camino Nuevo Academy #2	4
Camino Nuevo Charter Academy	3
Camino Nuevo Elementary No. 3	1
Canyon Elementary	5
Carpenter Community Charter	2
Celerity Dyad Charter	7
Celerity Nascent Charter	2
Celerity Octavia Charter	15
Celerity Troika Charter	30
Center for Advanced Learning	2
Children of Promise Preparatory Academy	2
Citizens of the World Charter	2
Colfax Charter Elementary	15
Community Magnet Charter Elementary	1
Equitas Academy Charter	2
Fenton Avenue Charter	49
Full Circle Learning Academy	20
Futuro College Preparatory Elementary	44
Gabriella Charter	7
Garr Academy of Math and Entrepreneuria	3
Global Education Academy	5
Goethe International Charter	2
ICEF Vista Elementary Academy	5
Ingenium Charter	11
Jardin de la Infancia	1
KIPP Empower Academy	1
KIPP Raices Academy	241

Larchmont Charter	2
Larchmont Charter-West Hollywood	3
Los Feliz Charter School for the Arts	6
Magnolia Science Academy 7	11
Marquez Avenue Elementary	3
Milagro Charter	15
Montague Charter Academy	15
Multicultural Learning Center	7
N.E.W. Academy Canoga Park	1
N.E.W. Academy of Science and Arts	1
New City	5
Ocean Charter	5
Open Charter Magnet	15
Our Community Charter	13
Pacoima Charter Elementary	1
Palisades Charter Elementary	2
San Jose Charter Academy	8
Santa Monica Boulevard Community Charter	3
Today's Fresh Start Charter	1
Today's Fresh Start Charter School Inglewood	73
Valley Charter Elementary	22
View Park Preparatory Accelerated Chart	2
Watts Learning Center	1
Westwood Elementary	13
Wilder's Preparatory Academy Charter	3
Wisdom Academy for Young Scientists	13

Table 8: Assessing the impact of geographic proximity and opening of charter schools on TPS performance

VARIABLES	(1) %ΔAPI	(2) %ΔAPI
distance_charter	***.0000339****	***-.0000204***
	(8.78e-06)	***(1.13e-05)***
count_charter	***-0.0543***	***-0.0366***
	(0.0239)	***(0.0170)***
year_of	***-0.217***	***-2.062****
	(0.852)	(0.696)
one_year_before	0.0858	-0.636
	(0.793)	(0.978)
two_year_before	-0.388	-1.547*
	(0.585)	(0.891)
three_year_before	0.178	-1.116*
	(0.487)	(0.602)
four_year_before	0.292	-0.226
	(0.500)	(0.508)
one_years_after	***-1.060***	***-1.779***
	(0.518)	(0.689)
two_years_after	-0.401	-0.563
	(0.886)	(1.017)
three_years_after	***-2.536****	***-2.872****
	(0.660)	***(0.827)***
four_years_after	***-1.927****	***-0.934***
	(0.697)	(0.785)
% minority	-0.153***	-0.156***
	(0.0369)	(0.0417)
% on free meals	-0.237***	-0.227***
	(0.0219)	(0.0282)
Pupils per teacher	-0.0439	-0.139
	(0.0353)	(0.108)
class_size	-0.187	-0.234*
	(0.117)	(0.132)
charter_enrollment		-0.00440***
		(0.00116)
charter_% on free meals		-0.0295**
		(0.0140)
charter_% minority		-0.0140
		(0.0204)
charter_API		0.000843
		(0.00393)
R-squared	0.859	0.855

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All columns include fixed year effects and four lags of the dependent variable. Also included in the model are indicators for majority ethnic group and controls for the distance to the nearest private school, and number of private schools within 5 miles.

Table 9: Endogeneity check

VARIABLES	(1) count	(2) distance	(3) year_of
% on free meals	0.0747**	-352.0***	-0.00398**
	(0.0348)	(130.9)	(0.00185)
% minority	0.0835*	-626.6**	0.0116***
	(0.0444)	(305.3)	(0.00417)
White	6.068***	-27,532***	0.223
	(2.256)	(6,633)	(0.221)
Asian	1.983	5,480	-0.103
	(1.671)	(8,092)	(0.100)
Black	1.374	-13,395*	0.0753
	(1.792)	(7,977)	(0.0780)
Other	8.278***	-32,073***	
	(1.065)	(6,442)	
API	0.00805	-104.4***	0.000664
	(0.00678)	(31.79)	(0.000656)
APIlag	-0.00739	7.759	-0.000647
	(0.00462)	(16.90)	(0.000819)
API2lag	-0.00668***	14.78	0.00126
	(0.00240)	(15.42)	(0.000885)
API3lag	-0.00562**	-12.29	-0.00176
	(0.00254)	(12.49)	(0.00111)
API4lag	-0.00175	-4.457	-0.000779
	(0.00421)	(15.39)	(0.000803)
API5lag	-0.00740***	18.22	0.000500
	(0.00189)	(15.42)	(0.000676)
API6lag	-0.0125**	7.613	-0.000952**
	(0.00521)	(13.61)	(0.000482)
%ΔAPI	-0.0584**	72.30	-0.00183
	(0.0290)	(103.9)	(0.00353)
%ΔAPI1lag	-0.0510***	72.64	-0.000596
	(0.0171)	(71.05)	(0.00328)
%ΔAPI2lag	-0.0457**	-22.76	-0.0102**
	(0.0200)	(98.12)	(0.00471)
%ΔAPI3lag	-0.0406	74.19	-0.000955
	(0.0272)	(90.01)	(0.00321)
%ΔAPI4lag	-0.0655***	115.4	0.00202
	(0.0164)	(94.45)	(0.00404)
%ΔAPI5lag	-0.0470**	37.28	-0.00302
	(0.0235)	(66.12)	(0.00291)
%ΔAPI6lag	0.00951*	14.64	0.00131*
	(0.00501)	(17.09)	(0.000696)
R-squared	0.123	0.073	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Year fixed effects are included in all models. Column 3 represents a probit model.

Figure 1: API distribution for charter schools

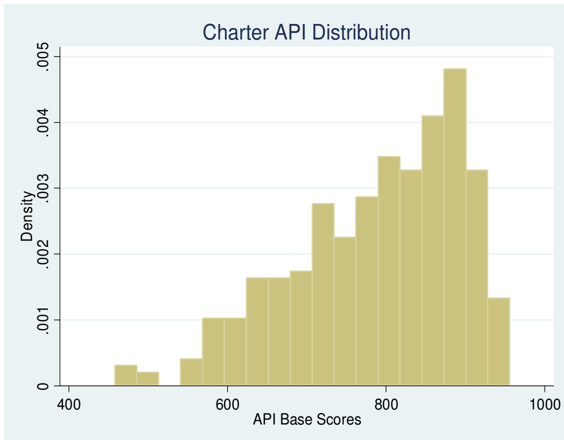


Figure 2: API distribution for traditional public schools

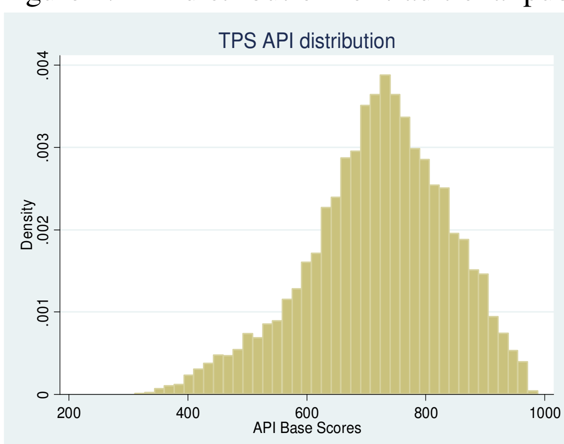


Figure 3: Distribution of Charter Schools' Opening

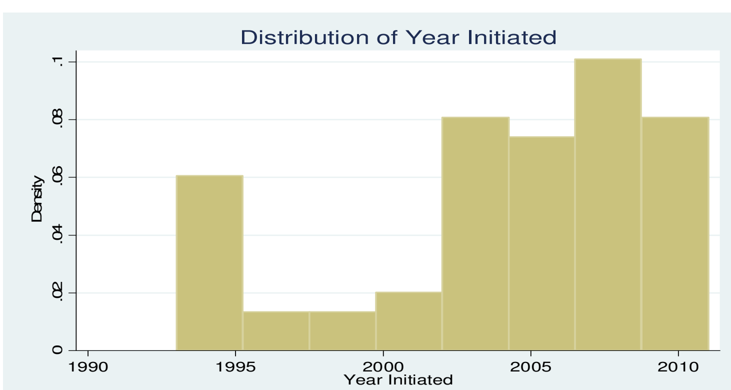
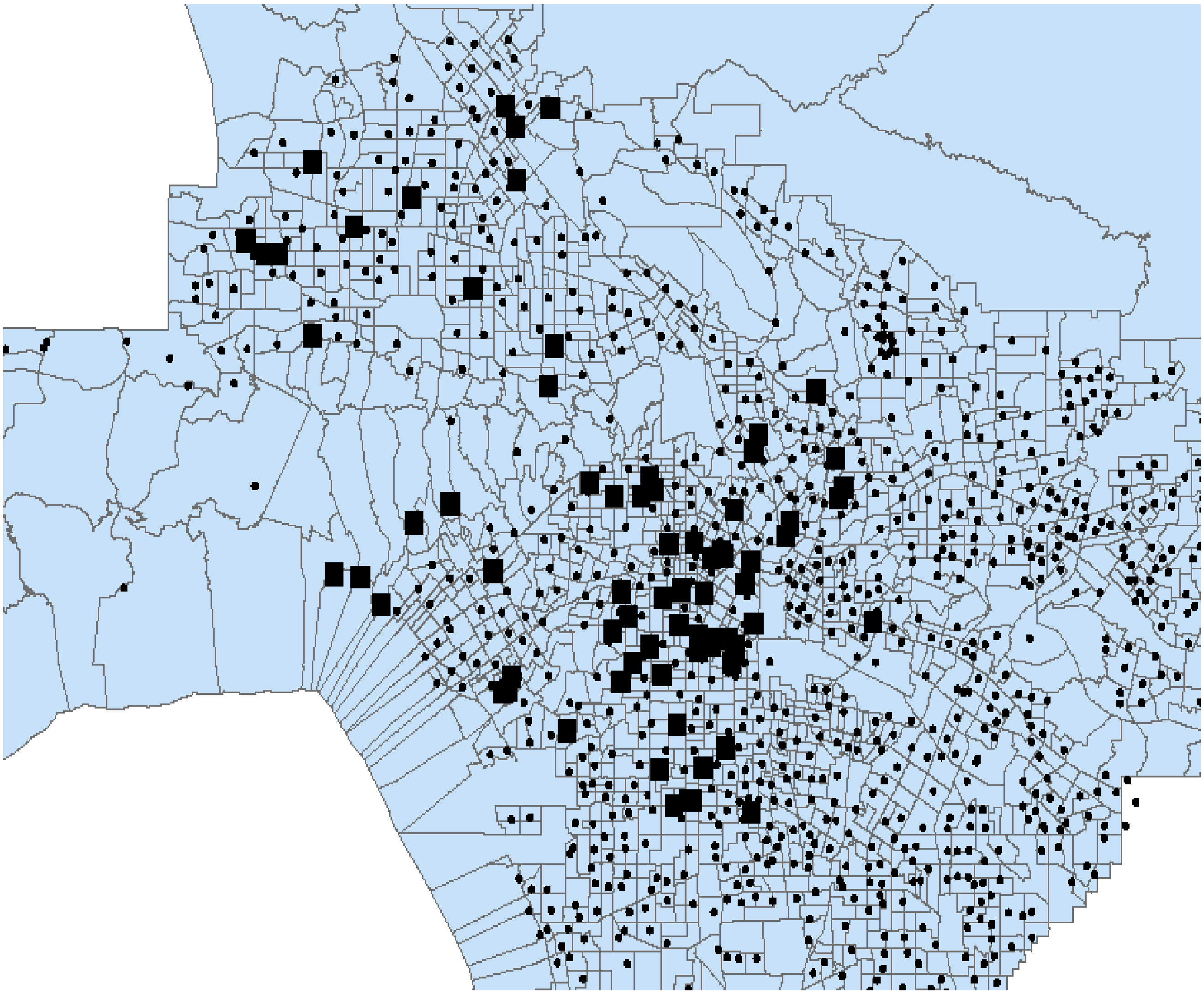


Figure 4: Location of TPSs and charter schools in LA County



Small circles represent traditional public elementary schools, while large squares represent elementary charter schools.

Figure 5: Histogram of distance from TPS to nearest charter school.

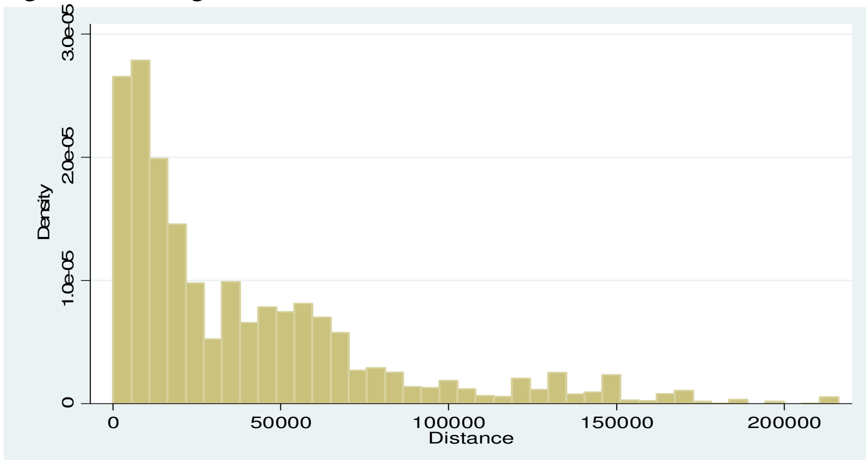


Figure 6: Histogram of the number of charter schools within 5 miles of TPS