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The Effects of School Type on Kindergarten Reading Achievement: Comparing Multiple Regression to Propensity Score Matching

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THE EFFECTS OF SCHOOL TYPE ON KINDERGARTEN READING

ACHIEVEMENT: COMPARING MULTIPLE REGRESSION TO PROPENSITY

SCORE MATCHING

by

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ABSTRACT

THE EFFECTS OF SCHOOL TYPE ON KINDERGARTEN READING ACHIEVEMENT: COMPARING MULTIPLE REGRESSION TO PROPENSITY SCORE MATCHING

by

Farrin D. Bridgewater

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BACKGROUND: Students taught at private schools by and large attain higher marks on reading achievement tests than do students taught at public schools. This difference is further aggravated by race, socioeconomic status, and reading ability at the entry of kindergarten.

PURPOSE: The goal of this nonexperimental study was to investigate whether students in either school type vary in reading achievement when they are measured on similar confounding variables (i.e., race, SES, and reading scores at the entrance of kindergarten).

METHODS: Propensity score matching, a method used to estimate causal treatment effect, was used to analyze the original sample of 12,250 kindergarten students. These same data were examined using hierarchical linear modeling (HLM).

RESULTS: Using PSM, the mean difference between private and public school students in their reading achievement in the spring kindergarten year was not statistically significant (mean difference = -.124, $t(6694) = .516$, $p = .606$).

CONCLUSION: Once students were equal on the confounding variables there was not a significant differences between the private school students and the public school students. Similar conclusions were reached by the PSM and the HLM methods.

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Introduction

Extant literature has shown that students attending private schools perform better than students attending public schools on academic tests (Carbonaro, 2006; Lubienski, Lubienski, & Crane, 2008; Boerema, 2009; Carbonaro & Covay, 2010; O'Brien & Pianta, 2010; Hallinan & Kubitschek, 2012). Several explanations for school differences are offered, including funding, accountability, and teacher quality. Despite gallant efforts (e.g. No Child Left Behind Act) to support better learning opportunities for low-performing public schools, research shows that private school students score one fifth of a standard deviation higher than public school students (Fryer & Levitt, 2004; Boerema, 2009). Also, the achievement gap between private and public schools emerges as early as kindergarten (Dagli & Jones, 2012; McWayne, Cheung, Green Wright, & Hahs-Vaughn, 2012).

One of the challenges in the investigation of school type on achievement is that such differences are always confounded by other variables, such as student's socioeconomic status [SES] (Tate, 1997; Magnuson & Duncan, 2006; Dagli & Jones, 2012), race (Caldas & Bankston, 1997; Tate, 1997; Ainsworth-Darnell & Downey, 1998; Kim & Hocevar, 1998; Herman, 2009; Burchinal, Steinberg, Friedman, Pianta, McCartney, Crosnoe, & McLoyd, 2011; Condron, Tope, Steidl, & Freeman, 2013), and their input reading ability at the entry of kindergarten (Butler, Marsh, Sheppard, Sheppard, 1982; Share, Jorm, Maclean, Matthews, 1984; McCoach, O'Connell, & Levitt, 2006).

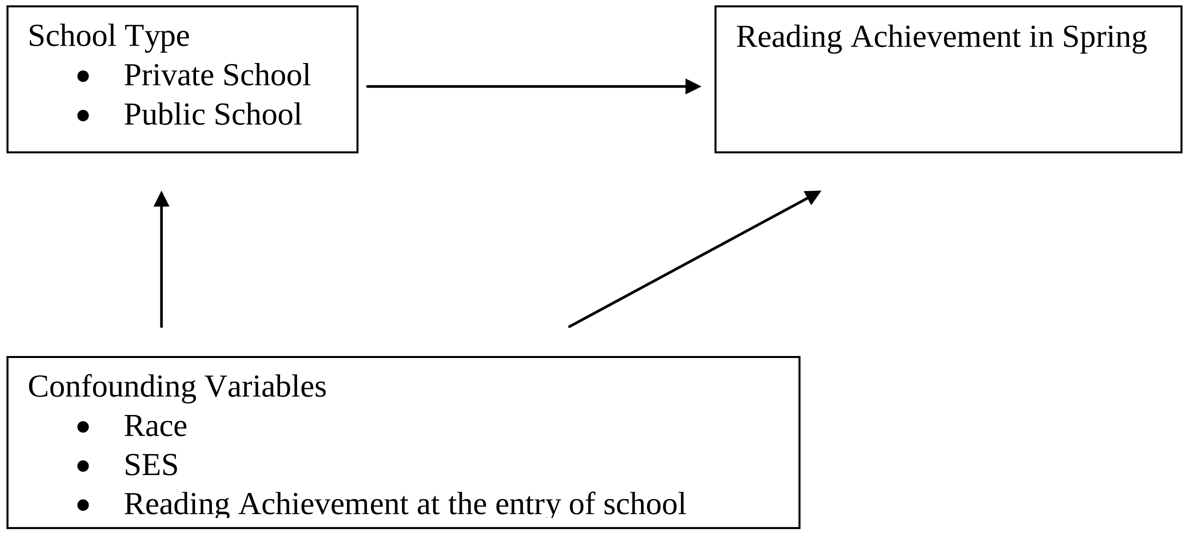
When we examine the effect of school type on achievement, we need to statistically control for these confounding variables because they are related to school type (i.e., the predictor) and achievement (i.e., the outcome) simultaneously. The ideal way of controlling for confounding variables is to conduct a randomized experiment. However, it is impossible to randomly assign people into different schools. Alternative approaches have been used to statistically control for these confounding variables. The most commonly used method is multiple regression (MR) analysis, which can estimate the partial effect of school type on achievement while controlling for the confounding factors or holding them constant.

There are several methodological inadequacies in previous studies that used MR analyses to examine the achievement gap between private and public schools. First, when school type and the confounding variables are used as predictors in a regression model, the regression coefficient of school type is interpreted as the mean difference in achievement between private and public schools with all the confounding variables being held constant. This interpretation is difficult to justify because a student's admittance to private or public school covaries with his/her values on those confounding variables. . Second, many studies were unable to obtain a nationally representative sample because of cost and time limitation. This increased the chance of error caused by selection bias and decreased generalization of studies. Third, in the context of school type on achievement, regression analysis is often inferred as causality (Caldas & Bankston, 1997; Plybon, Edwards, Butler, Belgrave, & Allison, 2003; Mistry, Biesanz, Chien, Howes, & Benner, 2008; O'Brien & Pianta, 2010; Dagli & Jones, 2012). This is a major problem in the reporting of results because it is misleading.

The use of propensity score matching (PSM) is proposed as a statistical method to evaluate the difference between private and public kindergarten students in terms of their reading achievement (Caliendo & Kopeing, 2008; Guo & Fraser, 2009), and compare the results based on PSM with the traditional MR results. Reading achievement of kindergarten students is chosen as the outcome variable because it is considered the most important prerequisite for later learning (Cooke, Kretlow, & Helf, 2010; Easton-Brooks & Brown, 2010; Al Otaiba, Folsom, Schatschneider, Wanzek, Greulich, Meadows, Li, & Connor, 2011).

The specific research question is as follows: if first-time kindergarteners in the public schools and those in the private schools are equal in terms of their SES, race, and reading ability at the entrance of kindergarten (i.e., the beginning of the fall semester), is there a difference in the mean reading achievement in the spring semester between these two types of schools? To answer the question, a nationally representative sample from the Early Childhood Longitudinal Study Kindergarten cohort (ECLS-K) will be utilized. PSM will be applied to match private and public school students in terms of their SES, race, and reading ability at the entrance of kindergarten for the fall semester. These same data will be analyzed using MR analysis for comparison purposes. Figure 1 presents the model upon which the analyses are based. The succeeding sections will disclose an introduction of PSM, a literature review of the confounding variables, followed by the methods, results, and discussion.

Figure 1: The Model



Literature Review

Propensity Score Matching

Drawing causal inference without randomization is a challenge. For example, an investigator may be interested in the treatment effects based on survey data that was collected without any randomized assignment rules (Guo & Fraser, 2009). The evaluation of these data would be infeasible and unethical as this would create a biased estimate of the treatment effect. To accurately measure the treatment effect for nonexperimental, non-randomized data, propensity score matching is often used. Propensity score matching is a method used to correct for differences in the treatment group and the control group due to selection bias.

The propensity score is defined as the “conditional probability of assignment to a particular treatment given a vector of observed covariates” (Guo & Fraser, 2009, p. 127). Fundamentally, all confounding variables are collapsed into a single, propensity score that ranges from 0.0 to 1.0 (Rojewski, Lee, & Gemici, 2010). The following equation defines propensity score (Equation 1):

$$e(x_i) = pr(W_i = 1 \,|X_i = \, x_i)$$

where the propensity score $e(x_i)$ is defined as the probability of an individual i being selected to the treatment condition (W_i = 1) given his/her values on the confounders **X**. The vector **X** has the potential to include many confounders. One advantage of the propensity score is that it provides a natural weighting scheme that is especially useful when the dimensionality of the confounders is high (Guo & Fraser, 2009, p. 132).

Participants in the control (i.e. public schools) and the treatment (i.e. private schools) groups are matched based on similar propensity scores and unmatched participants are dropped. Based on matched participants, we can obtain an estimate of the average treatment effect or the difference in mean outcomes between the treatment and control groups (Caliendo & Kopeing, 2008, p. 38). A series of practical steps are recommended for the implementation of propensity score matching. In the subsequent sections each step is detailed.

Variable Choice. The selection of variables is the most critical step in the matching process. In deciding which confounders to include or exclude in the propensity score model, specific criterion are stipulated. First, only variables that simultaneously influence the participation in the treatment groups and the outcome of interest should be included when estimating the propensity score. Secondly, only variables that are unaffected by participation are to be included in the model (Caliendo & Kopeing, 2008; Rojewski, Lee, & Gemici, 2010). Therefore, variables should be fixed over time or measured before participation.

Choosing appropriate confounders is crucial because omitting important variables can cause included confounders to be unbalanced for the private and public school groups. Yet, adding extraneous variables can increase variance of the propensity scores. If an investigator is uncertain about which variables are best when estimating the propensity score, three statistical techniques can be used to select the appropriate variables: hit or miss, statistical significance or the leave-one-out cross validation method. The hit or miss method picks variables that will "maximize the within-sample correct prediction rates" (Caliendo & Kopeing, 2008, p. 39). Statistical significance, which can be used in conjunction with the hit or miss method, requires that a variable only be kept when it reaches conventional level of significances. The leave-one-out cross validation method is similar to the statistical significance method in that the mean square error of additional variables is compared based on goodness of fit.

Estimating the Propensity Score. The most common method used to estimate the propensity score is binary logistic regression. The conditional probability of participating in the private school group for *i*th participants (W_i= 1) given $\boldsymbol{X_i}$ can be computed (Equation 2):

$$P\ (W_i\ |\boldsymbol{X}_i = \boldsymbol{x}_i) = \frac{e^{\boldsymbol{x}_i \boldsymbol{\beta}_i}}{1 + e^{\boldsymbol{x}_i \boldsymbol{\beta}_i}}$$

using the regression coefficients $\boldsymbol{\beta}_i$, the predicted probability of participating in the treatment condition (i.e., the propensity score) is realized for each participant (Guo & Fraser, 2009, p. 136). The best logistic regression model produces a propensity score that balances the two groups on the observed confounding variables. If cofounders are imbalanced, logistic regression should be rerun with high-order terms.

Matching Algorithm. After the propensity scores are computed, each private school participant is matched to *n* public school participants based on the propensity scores. The goal of matching is to ensure that the private school and the public school groups are balanced in terms of the cofounders. Depending on the sample size and the distribution of the propensity scores, two conventional strategies can be employed to match participants. The next two subsections describe greedy matching and optimal matching procedures.

Greedy Matching. Creating a "new sample of cases that share similar likelihoods" of being assigned to the private school group is termed greedy matching (Guo & Fraser, 2009, p. 145). Under the greedy matching umbrella are nearest neighbor (NN) matching and caliper matching. NN matching involves a participant from the public school group to be matched to a participant from the private school group based on similar propensity scores (Guo & Fraser, 2009). Propensity scores for participant *j* and participant *i* are neighboring because the difference of propensity scores is the smallest among all possible matches.

The second matching algorithms is caliper matching. By imposing a tolerance level on the propensity score bad matches are avoided and the quality of matching is improved. Individual cases are matched according to the "propensity range" which indicates the proximity of the propensity score (Caliendo & Kopeing, 2008). Conversely, if only a few matches can be found then the variance of the estimates will increase. Another drawback of caliper matching is that it is difficult to ascertain a tolerance level that is reasonable.

Optimal Matching. Optimal matching is a better approach than greedy matching because it finds the most desirable pairing of propensity scores by minimizing the total distance between the private school group and the public school group. Guo and Fraser (2009, p. 150), demonstrate this using the following propensity scores: .1, .5, .6, and .9.

Greedy matching pair's propensity scores according to their proximity. Thus, the second and third participants would be pair first because their distance is the smallest (i.e. $|.5 – .6| = .1$). Next, the first and fourth participants would be matched (i.e. $|.1 – .9| = .8$). Therefore, the total distance on propensity score is $|.5 – .6| + |.1 – .9| = .9$. On the other hand, optimal matching pairs the first and second participants ($|.1 – .5| = .4$) to form the first pair and the third and fourth participants ($|.6 – .9| = .3$) to form the second pair. The optimal matching gives a total distance of $|.1 – .5| + |.6 – .9| = .7$, which is sufficiently better than that derived from greedy matching. By minimizing the total distance, the prospect of one pairing being much superior or inferior to another is less likely.

Conceptually, the optimal matching process is fairly simple. The matching process generates matched sets so that there are a set of participants in the treatment group and a set of participants in the control group. According to Haviland, Nagin, and Rosenbaum (2007), pairing each participant in the treatment with two controls is more efficient than a one-to-one match. Thus, within each matched set, one participant in the private school group will be matched to two participants in the public school group. The private school participant will be similar to the public schools in terms of propensity scores for each matched set. The application of this method reduces bias, increases efficiency and decreases variance (Guo and Fraser, 2009).

Assessing Matching Quality. The distribution of the propensity scores needs to be assessed to establish whether or not the private school and the public school groups are balanced for the selected cofounders. Initially, we expect differences between these two groups however, after matching, the variables should be balanced. Methods used to assess the matching quality vary with the methods used for matching. When optimal matching is used, the absolute standardized difference for confounding variables, developed by Haviland et al (2007), is often used to check imbalance on a confounder *x* for the private school and public school groups before and after matching. More specifically, the absolute standardized difference before matching (d_x) is computed by (Equation 3):

$$d_x = \frac{|Mx_t - Mx_p|}{S_x}$$

where Mx_t represents the mean of *x* in the private school group and Mx_p the mean of *x* in the public school group before matching. The overall standard deviation S_x represents the standard deviation of private and public school groups combined. After matching, the level of imbalance on the confounder *x* should be estimated (Equation 4):

$$dx_m = \frac{|Mx_t - Mx_c|}{S_x}$$

where Mx_c represent the mean of the public school group after matching. It is expect that $d_x > dx_m$ as the sample balance should improve after matching (Guo & Fraser, 2009). For example, in their study of peer-rated popularity, Haviland et al. (2007) reported $d_x = 0.47$ for the cofounder before matching and $dx_m = 0.18$ after matching. Hence, the treatment and control groups were initially almost half a standard deviation apart on the confounder before matching. The difference between the groups after matching is 18% of a standard deviation for the confounder, indicating that the matching improved balance.

Common Support. The treatment and the control groups should overlap in terms of the distribution of the confounding variables. A straightforward way to do this is to visually analyze the density distributions of the propensity score for both groups. More complex procedures like the minima and maxima comparison ensure common support regions for the treatment and control group (Caliendo & Kopeing, 2008; Rojewski, Lee, & Gemici, 2010). For example, if the propensity score for the private school group is within the interval [0.08, 088] and within the interval [0.04, 074] for the public school group, under the minima and maxima comparison the common support region is within [0.08, 0.74]. Observations outside of the interval should be discarded from further analysis. If the proportion of participants discarded is large, the remaining participants are less representative of the estimated effect.

Outcome Analysis. After matching, an estimate of the average treatment effect (mean differences) for the total number of sample participants *N*, should be assessed by (Equation 5):

$$\hat{\delta} = \sum_{i=1}^{b} \frac{n_i + m_i}{N} [\bar{Y}_{0i} - \bar{Y}_{1i}]$$

where *i* indexes the *b* matched strata (i.e. levels), n_i and m_i represent the number of participants in the private school group and the public school group in stratum *i* respectively, and $\bar{Y}_{0i}$ and $\bar{Y}_{1i}$ represent the mean outcome in the public school and private school groups in stratum *i* respectively (Guo & Fraser, 2009, p. 158). A significance test of the average treatment effect may be performed using the Hodges-Lehmann aligned rank test (Hodges & Lehmann, 1962).

The average treatment effect can also be computed using a “special type of regression adjustment” (Guo & Fraser, 2009, p. 159). By taking the difference scores on the outcome variable *Y* for the matched private school and public school participants $Y = Y_1 - Y_o$ and the difference scores on the confounding variables **X** for the matched private school and public school participants $\boldsymbol{X} = \boldsymbol{X}_1 - \boldsymbol{X}_o$, the estimated regression function is derived $Y = \hat{\alpha} + \boldsymbol{X'}\widehat{\boldsymbol{\beta}}$. The estimate of the average treatment effect is denoted $\hat{\alpha}$. Using the observed *t* statistic and *p* value associated with $\hat{\alpha}$ a significance test is performed.

Confounding Variables in the Comparison of Public vs. Private Schools

Confounding variables are extraneous variables identified through theoretical and empirical research as being related to the independent and dependent variables. The following confounding variables were chosen based on the literature which advocates for the inclusion of such confounders when studying the difference between public schools and private schools in term of students' achievement. Too, it was imperative that these confounding variables fit the rules and assumptions of MR and PSM analyses.

Race. Racial differences in student achievement are well documented in the literature. African American students (black, non-Hispanic) generally perform worse on academic tests than do European American students (white, non-Hispanic) (Caldas & Bankston, 1997; Tate, 1997; Ainsworth-Darnell & Downey, 1998; Kim & Hocevar, 1998; Herman, 2009; Burchinal et al, 2011). African American students by and large receive lower scores on reading measures than do European American students. Using the Early Childhood Longitudinal Study to analyze gaps in kindergarten reading achievement, Chatterji (2006) found that African American students performed about 0.335 standard deviations lower than that of European American students. Over time the achievement gap for this sample of students continued to expand as African American students performed about half a standard deviation below European American students by the first grade.

The fact that African American students are continuously outperformed by their European American counterparts is puzzling to many. However, recent work on racial difference has revealed school type as a major obstacle to achievement for African American students. African American students are more likely to attend public schools than European American students who are more likely to attend private schools (Lankford & Wyckoff, 1992; Sander, 1996; Fairlie & Rssch, 2002). In a study of racial differences and school type (Saporito, 2009) empirical results indicated a “positive, strong, and consistent association” between European American students and enrollment into a private school (p. 188). In contrast, the association for African American students and private school enrollment is described as weak. Condron and fellow investigators (2013, p. 132) explains that school type intensifies the achievement gap for African and European American students in that it creates “resource-rich environments for white students and resource-poor educational environments for black students”. Further studies (Caldas & Bankston, 1997, 1998; Williams, Davis, Miller Cribbs, Saunders, Herbert Williams, 2002; Saporito & Sohoni, 2006) support this claim in that the achievement gap between races is narrowed when African and European American students attend the same schools, be it public or private.

Socioeconomic Status. While there is no agreement on the conceptual meaning of SES, the variable is operational through family income, parental occupation, and parental education. Research has shown such factors to be predictive of student achievement (Tate, 1997; Davis-Kean, 2005; Magnuson & Duncan, 2006; Davis-Kean & Sexton, 2009). This relationship is referred to as the socioeconomic gradient because it details the gap in student achievement for low and high SES (Caro, McDonald, &

Willms, 2009). Generally, lower SES is indicative of lower achievement. Pungello and colleagues (2009) found SES to be a predictor of expressive language for students entering kindergarten. Students from lower SES had a slower rate of growth than students from higher SES. Another study examined the reading trajectories of students from kindergarten to third grade. Results revealed that SES predicted initial reading achievement, and reading achievement over the span of first, second, and third grade (Aikens & Barbarin, 2008). Many speculate that the impact SES has on achievement is attributed to the lack of resources. Students from lower SES receive fewer educational resources because of limited access to information about schools and thus are less likely to attend schools outside of their disadvantaged neighborhoods (Ediger, 2008).

On the contrary, conflicting studies suggest that SES has little to no impact on student achievement. For instance, Caro, McDonald, and Willms (2009) studied SES on student achievement for Canadian students from birth to adulthood. Results suggest that during elementary school, achievement is invariant and is not contingent upon SES. A similar study (Mistry et al., 2008) explored SES differences in cognitive achievement for student. Using longitudinal data, investigators reached findings similar to those in the Caro, McDonald, and Willms (2009) study. That is, students SES did not directly impede their cognitive achievement.

Additional studies sustain the above in that many students are achieving academic success at or above conventional norms despite lower SES. Caldas and Bankston (1997) demonstrated this in their study of poverty status and achievement. Results indicated that lower SES students who attended classes with higher SES students achieved at a level that was not normal for this group of students. Another study (Herbers, Cutuli, Supkoff, Heistad, Chan, Hinz, & Mastern, 2012) of poverty and academic achievement concluded that students who received free or reduce lunch performed better on reading test than students who did not receive free or reduced lunch. Such findings are surprising for the reason that students who live below the poverty line, termed "very poor", typically score 7 to 12 point lower than "near poor" students (Lacour & Tissington, 2011).

Family SES also influences school attending decisions. Until recently, enrollment into private or public school totally depended upon family SES. Students from middle and higher socioeconomic families could choose to live in affluent neighborhoods with good schools or send their child to private schools. Comparably, lower socioeconomic families were restricted to neighborhood schools without alternative choices (Levin, 1998). Lauren (2007) concluded that students living in lower SES neighborhoods have a decreased chance of attending private schools than student living in higher SES neighborhoods. However, the implementation of new policies and programs, such as the Milwaukee Voucher Program, allows lower SES students to attend (nonsectarian) private schools and public schools in Milwaukee with public funds. Accordingly, in the first year that the program was initiated, the enrollment in private schools rose from 341 to 830 (Levin, 1998). In a different study which examined tuition free public schools and competitive, tuition-financed private schools, Epple and Romano (1998) reported that private schools attract lower income, high achieving, students by offering discounted tuition. In my literature review, a single study reported that SES was not a statistically significant predictor of school type for kindergarten students (Carbonaro, 2006).

Reading Achievement at the Entry of Kindergarten. The body of research examining reading ability at the entry of kindergarten on achievement is minimal. That notwithstanding, the consensus is that early reading achievement predicts later reading achievement (Butler, Marsh, Sheppard, Sheppard, 1982; Lonigan, Burgess, Anthony, 2000; Ritchey, 2004; McCoach, O'Connell, & Levitt, 2006). Measures of reading acquisition are especially valuable in longitudinal research. Studying reading ability of 545 kindergarten students, Pope, Lehrer, and Stevens (1980) found a moderate correlation (r = .50) between reading scores in kindergarten and reading scores in the fifth grade. A different study (Share, Jorm, Maclean, & Matthews, 1984) looked at the reading achievement of first time kindergarten students. Measuring sight words, nonsense words, spelling, and scrambled story words, investigators found that early reading ability was a strong predictor of reading achievement in kindergarten and first grade. In my review of the literature, a single study (Badian, 1988) assessed reading before the entry of kindergarten. Here the results suggested two important points: (1) early reading ability predicts later reading achievement, and (2) students have higher reading scores when educated at the same schools, be it private or public.

The principal assertion addressed by empirical data implies a relationship between reading ability at the entry of school and schools type. However, this difference is noticeable before entrance into private or public schools (Coleman, Hoffer, Kilgore, 1982; Rathbun, West, Hausken, 2004; Datar, 2006). A landmark study (Topping & Paul, 1999) of self-assessed reading comprehension at the beginning of kindergarten for 659,000 students statewide found stark differences in private and public schools. The 608,338 public schools students had a mean reading score of 19.34, while the 50,876 private school students had a mean reading score of 33.24. Such a large difference may be attributed to differences in reading practices at home (e.g., reading out loud or to oneself, type of book, time spent reading each day, etc). Another study which compared early reading ability (phonemic awareness) and school type showed that kindergarten students in private schools performed better on reading tests than kindergarten students in public school when tested in the first months of school (Snider, 1997).

Summary

Propensity score matching corrects for the imbalance between the treatment condition and the control condition in the covariates due to selection bias. By pairing participants in the private school group and participants in the public school group on the confounders, a less biased estimate of the treatment effect is established. These confounders simultaneously influence enrollment into private or public school as well as influence reading achievement. Too, the confounding variables in the model are unaffected by the treatment group. Otherwise stated, although student's race, SES, or reading ability at the entry of kindergarten influence enrollment, these variables are not affected by enrollment into private or public school. Therefore, these confounders are appropriate for propensity score matching.

Methods

Data

The Early Childhood Longitudinal Study Kindergarten class of 1998–1999 (ECLS-K) was used for this study. Sponsored by the National Center for Education Statistics (NCES) the data provides information on children's readiness at entry of kindergarten. Additional objectives are: (1) Measuring the trajectory of achievement; (2) Cross-sectional analysis of the quality of kindergarten programs; and (3) Assessing family, community, and school experiences on child physical, emotional, social, and cognitive development. The ECLS-K has both descriptive and analytic purposes.

Participants

Approximately 12,250 first time kindergarteners were included in the sample. The average age of kindergartens was 5.6 years. African American students (17.9%) represented a small portion of the kindergarten sample, as more than half of sample of students is European American (74.1%). Hispanic students (8.0%) were also represented in the sample. Students attending public schools (76.3%) outnumbered students enrolled in private schools (23.7%). A smaller percentage of Black (9.8%) and Hispanic (6.9%) students attended private school. About half of the students were female (49.9%). The sample is diverse in terms of socioeconomic status. Listwise deletion was used to exclude any missing data from the analysis.

Measures

Predictor: School Type. A total of 2,900 private and 9,350 public schools from the Midwest, Northeast, West, and South regions are included in the ECLS-K database. By definition the distinction between public and private schools is governance based. Public schools are run by publicly elected school boards. Private schools are governed by members of the schools association (Carbonaro, 2006; Boerema, 2009). In the study, private schools are the treatment group and public schools are the control group. Data was delimited to included students who did not change schools during the fall and spring kindergarten year.

Criterion: Reading IRT Scale Scores in the Spring of the Kindergarten year. Item response theory (IRT) is a model used to score tests that measure's ability or potential aptitude. IRT computes score's by establishing right-wrong patterns. Items are administered based on the correct or incorrect answer given for a previous question. This pattern is best for estimating achievement. There are 72 items for the reading IRT scale score. The mean for this scale is 22.0 and the standard deviation is 8.3. The reliability of the criterion-referenced measure is 0.95 for spring kindergarten year (National Center for Education Statistics, 2001).

Matching variables

Race/Ethnicity. The variable race consists of three categories: White, Black, and Hispanic. When used in the analysis, this variable is dummy coded with White as the reference group.

Child Socioeconomic Status. This variable is computed to reflect household level SES at the time of data collection in the spring of kindergarten. The components used to create the variable are (1) parental education; (2) parental occupation; and (3) household income (National Center for Education Statistics, 2001)

Reading IRT Scale Scores in the Fall of the Kindergarten year. IRT scale scores for the fall kindergarten year is the third confounder for the model. Measured in the early fall semester, the IRT scale scores are an efficient gauge of students input reading achievement. Similar to the spring reading IRT scale, the fall IRT scale has high reliability (0.93) (National Center for Education Statistics, 2001).

Analytic Plan

PSM. To fulfill the objectives of this study, PSM analyses will be performed. PSM will correct for differences in the private school group and the public school group due to selection bias. The propensity scores are computed (Equation 6):

$$P\ (W_i\ |\boldsymbol{X}_i =\ \boldsymbol{x}_i) = \frac{e^{\beta_0+Black_i\beta_1+Hisp_i\beta_2\ +SES_i\beta_3+IRTfall_i\beta_4}}{1+\ e^{\beta_0+Black_i\beta_1+Hisp_i\beta_2\ +SES_i\beta_3+IRTfall_i\beta_4}}$$

After obtaining the propensity scores, the one-to-two ratio optimal matching algorithm (i.e., one student in private schools matched with two students in public schools) will be used because it is more efficient than a one-to-one match (Haviland et al., 2007). The optimal matching algorithm will be implemented using SAS 9.3. This program is used to perform multivariate logistic regression which calculates and saves the predicted propensity score for participants in both groups. The propensity score represents the relationship between the confounding variables and the criterion variable. Once this is carried out, the matching quality in terms of the balance on race, SES, and reading IRT scale scores in the fall of the kindergarten year will be estimated using Equation 3 and 4. Finally an Independent Samples T-Test for the average treatment effect will be performed.

MR. Multiple regression analysis is a fairly malleable data analytic system and therefore commonly used to estimate the criterion (*Y*) and its relationship to the predictors ($X_1 \ldots X_p$). MR can measure the “magnitude of the total effect of a factor on the dependent variable as well as of its partial relationship, that is, its relationship over and above that of other factors” (Cohen, Cohen, West, Aiken, 2002, p. 2). Due to the multilevel structure of the data (i.e., students nested within schools), a hierarchical linear regression model will be used to estimate the effect of school type controlling for the confounding variables. The model is specified as (Equation 7 and Equation 8):

Level-1: $Y_{ij} =\ \beta_{0j} + \beta_1 Black + \beta_2 Hisp + \beta_3 SES + \beta_4 IRTfall + e_{ij}$

Level-2: $\beta_{0j} =\ \gamma_{01} + \gamma_{00} schooltype + u_{0j}$

where *i* indexes students and j indexes schools. Level-1 identifies the intercept and slope within each group. Level-2 identifies the groups alongside the intercept and slope within each group obtained from the first regression equation. Both the level-1 residual (e_{ij}) and the level-2 random effects (u_{0j}) are assumed to be normally distributed and independent from each other.

Results

PSM

Results from logistic regression which produce the predicted propensity score of each matched set for the reading IRT scale scores in the spring semester of the kindergarten year are given below. Differences between groups were evaluated using a t-test for continuous variables and a Chi-squared test for categorical variables. Table 1 gives the descriptive statistics and cross-tabulation for the original sample of students. For all confounding variables there is a statistically significant difference between private schools and public schools ($p < .001$). Kindergarten students in private schools were more likely to have higher reading IRT scale scores in the fall as well has a higher SES than kindergarten students in public schools. The matched sample (Table 2) contrasts from the original sample in that race, SES, nor reading IRT scale scores in the fall kindergarten year is statistically significantly different at the 0.001 level for the groups. This suggests that the two groups are closely matched on the confounding variables and thus more alike than different.

Table 1: Original Sample

	Private School	Public School	p value	Cohen's *d*
Total Participants	**2900 (23.7%)**	**9350 (76.3%)**		
Race/Ethnicity			< .001	
White	2416 (83.3%)	6664 (71.3%)		
Black	283 (9.8%)	1913 (20.5%)		
Hispanic	201 (6.9%)	773 (8.3%)		
SES	.5251 ± .68	-.0071 ± .75	< .001	.743
Fall Reading IRT Scale Scores	25.95 ± 8.82	21.89 ± 7.99	< .001	.482
*** Spring Reading IRT Scale Scores	36.09 ± 10.40	31.83 ± 9.89	< .001	.419

***Criterion Variable

Table 2: Matched Sample

	Private School	Public School	p value	Cohen's *d*
Total Participants	**2232 (33.3%)**	**4464 (66.7%)**		
Race/Ethnicity			.101	
White	1805 (80.9%)	3720 (83.3%)		
Black	261 (11.7%)	412 (9.2%)		
Hispanic	166 (7.4%)	332 (7.4%)		
SES	.29 ± .54	.28 ± .54	.449	.018
Fall Reading IRT Scale Scores	24.06 ± 7.07	23.77 ± 7.59	.128	.039
*** Spring Reading IRT Scale Scores	34.17 ± 9.15	34.05 ± 9.37	.606	.013
Propensity Score	.7417 ± .0997 (.42, .95)	.7434 ±.0987 (.42, .96)		

*** Criterion Variable

Figures 2, 3 and 4 show the boxplots and histograms of the propensity scores by private and public school groups. The two groups have a high degree of overlapping in terms of the distribution of propensity scores. Beyond visual congruence, the distribution of the propensity scores also shows that the private school and public school groups are balanced for the selected confounding variables. Before optimal matching, the absolute standardized difference for SES was 0.74, meaning that the private school group and the public school group are a less than half a standard deviation apart on this confounding variable. After optimal matching, the absolute value is 0.02, meaning the difference between the two groups is 2% of a standard deviation for race. Table 3 shows the two remaining confounders. The difference between the groups indicates that the imbalance after matching is sufficiently better than before optimal matching.

Table 3: Before and After Optimal Matching

	d_x	d_{xm}
Race	--	--
SES	.742	.018
Fall Reading IRT Scale Scores	.482	.039

Figure 2: Boxplots

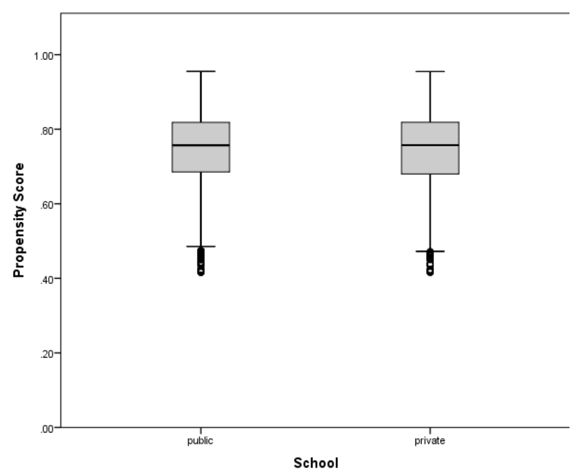


Figure 3: Private School

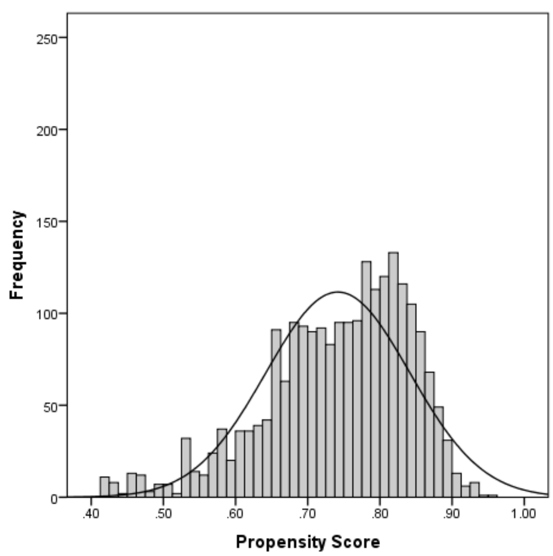
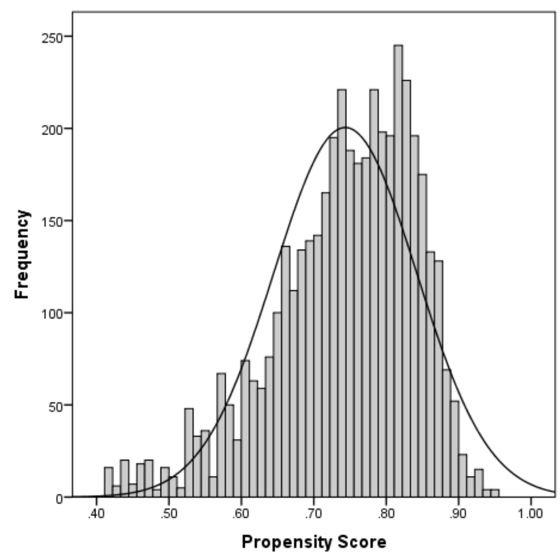


Figure 4: Public School



The average treatment effect for the outcome variable reading IRT scale scores in the spring kindergarten year is not statistically significantly different for students in private and public school groups. Comparing the reading IRT scale scores in the spring kindergarten year for the private school group (M = 34.17, SD = 9.15) and the public school group (M = 34.05, SD = 9.37), the Independent Samples T-Test reports that school type does not affect reading IRT scores in the spring kindergarten year (t(6694) = .516, p = .606).

MR

Table 4 shows the correlations for the variables based on the original sample. Reading IRT scale scores in the fall and spring semester for the kindergarten year are strongly correlated (r = .799, p < .001). SES and private school attendance was moderately correlated (r = .294, p < .001). Too, SES and Black students are moderately correlated (r = -.270, p < .001) while SES and Hispanic shows a weaker correlation (r = -

.093, p < .001). There was a non-significant correlation of -.021 (p = .020) between Hispanic students and private school attendance.

Hierarchical linear modeling was conducted to examine the relationship between the reading IRT scale scores in the spring kindergarten year with race, SES, and the reading IRT scale scores in the fall kindergarten year for student in private and public schools. All confounding variables were significant predictors in the model except for the dummy variable representing Hispanic students. More specifically, reading IRT scale scores for the fall kindergarten year (b = 0.93, p < .001) and SES (b = 0.61, p < .001) had positive effects on the outcome variable. Black students tended to have lower scores on the outcome compared to white students (b = -1.10, p < .001). Controlling for the confounders, private school attendance is not a significant predicator (b = -0.10, p = .651). Therefore, attending private school has no effect on students IRT scale score for the spring.

Table 4: Correlations

	Spring Reading IRT Scale Scores	Fall Reading IRT Scale Scores	Black Students	Hispanic Students	SES
Fall Reading IRT Scale Scores	.799				
Black Students	-.165	-.147			
Hispanic Students	.036	-.069	-.137		
SES	.345	.379	-.270	-.093	
Private School	.179	.206	-.119	-.021	.294

Table 5: Hierarchical Linear Model

	B	Standard Error	*t*	*p value*
Intercept	11.60	.198	58.41	< .001
Fall Reading IRT Scale Scores	.935	.006	134.39	< .001
SES	.611	.083	7.33	< .001
Black Student	-1.10	.182	-6.04	< .001
Hispanic Student	.263	.211	1.24	.213
Private School	-0.10	.239	-0.45	.651

Discussion

The purpose of this paper was to present PSM as a method used to estimate the difference between private and public kindergarten students in terms of their reading achievement in the spring semester of their kindergarten year. In particular, PSM highlights that the comparison of private and public school students is initially inadequate as the two groups are largely unalike in the original sample. The propensity score method is able to rectify this imperfection by pairing the public school group with the private school group based on the propensity score, which is the probability of attending private schools conditional on the confounding variables. The matched sample is more alike than the original sample. The absolute standardized difference shows that the imbalance of confounding variables is reduced after matching. Taking reading IRT scale scores in the fall of the kindergarten year as an example, before matching, the private school group and the public school group differed 48% of a standard deviation, whereas after matching, bias was reduced to 4% of a standard deviation. Because the two groups are more balanced on the confounding variables (i.e., the two groups are more comparable), the difference between the two groups in terms of the outcome of interest has an improved estimate (Hahs-Vaughn & Onwuegbuzie, 2006).

In the original sample, public school students achieved significantly lower than private school students in terms of their reading ability in the spring semester. However, the estimated average difference between private and public students was not statistically significant based on the matched sample. The result was consistent with that obtained by using the multilevel regression model. This indicates that the difference in the outcome of interest that existed in the original sample might be due to the confounding variables such as student race, SES, and their reading ability at the entry of kindergarten, rather than school type. After adjusting for these confounding variables, either by using PSM or the multilevel regression analysis, school type had no significant effect on student achievement. It should be noted that although the same conclusion was reached by using PSM and the multilevel regression analysis in this study, these two methods are of different nature and the results based on these two methods are not always consistent.

This study sheds light on the current programs and practices' concerning the effect school type has on kindergarten reading achievement. Beyond the scope of this work are the social, economic, and cultural questions that remain unanswered. Many studies (Caldas & Bankston, 1997; Tate, 1997; Ainsworth-Darnell & Downey, 1998; Kim & Hocevar, 1998; Herman, 2009; Burchinal et al, 2011) suggest that African American students preform worse than European American students. Other studies (Tate, 1997; Davis-Kean, 2005; Magnuson & Duncan, 2006; Davis-Kean & Sexton, 2009) point to SES as a predictor of achievement. And again additional literature (Butler, Marsh, Sheppard, Sheppard, 1982; Lonigan, Burgess, Anthony, 2000; Ritchey, 2004; McCoach, O'Connell, & Levitt, 2006) finds early reading achievement to be predictive of later reading achievement. The results from this study clearly show that race, SES, and reading ability at the entry of school need to taken into consideration when evaluating the effectiveness of public and private schools. Policymakers should consider these findings when implementing change into the educational system.

Limitation and Future Research

Collectively, the degree to which the findings of PSM and the MR (i.e. hierarchical linear model) analyses of this study are generalizable is of concern as the techniques employed to answer the research question are specific to the study. According to Ferron and fellow investigators (2004, p. 10), limitations (alike to those previously detailed) influence the "breadth and depth of the inferences made". Measures however, can be taken to examine the strength of the findings of this work. For example, cross-validation is needed to ascertain the validity of the model. By partitioning a sample of data into subsets of data, one subset of data is used to estimate the model and the second subset is used to assess how well the model performed. Another means of addressing generalizability is to conduct what is known as a sensitivity analysis. This type of analysis determines "what the unmeasured covariate would have to be like to alter the conclusion of a study" (Guo & Fraser, 2009, p. 298). Unambiguously, the sensitivity analysis can test for the robustness of the results, find errors in the model, detect nonstandard distributions, and establish the degree to which the model fit and parameter remain constant (Ferron et al, 2004).

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