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Impact of School Type On Student Academic Achievement

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Abstract

This study aims to investigate the causal effects of school type on the student achievement. Schools type involves two categories: public schools and private schools; whereas student achievement is defined in terms of an overall measure named as Basis for Admission Score (BAS), which is a weighted score reflecting both the grades obtained from courses in each school and the points obtained at nation-wide centralized exams. Factors used as controls in the study include gender of the student, parental attributes (are they alive and live together; their levels of education and occupations), type of the house (own/rent/public housing), separate room of the student, city the family lives in and the level of development of the geographical region. This study utilizes a dataset comprising 3,752,374 secondary school students, which covers all of the student population of Turkish secondary schools within 2014-2016 period. This comprehensive dataset is utilized for the first time in such a study.

At the first step, we present the literature on the effects of school type on academic achievement measured by test scores. This literature can be traced back to 1960's. On the other hand, a second line of literature, which focuses on the evaluation of causal effects of policies and of programs has progressed swiftly starting from 1980's and promises an important methodological framework for evaluation of policies and programs in education science. The methodology of this study is designed by bringing together the mentioned two lines of research. Methodology involved the application of regression adjustment, inverse probability weighting, and exact matching techniques in a complementary style in order to ensure the robustness of estimations.

Under the assumptions discussed in detail in the study, we have found that school type has significant impact on student achievement in Turkey. Being a private school student instead of public school student leads to 87 points increase (29.6%) on average in BAS score. It is found that school type has a comparatively larger

Keywords

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effect in Turkey compared to other country examples. Based on the findings of the study, a set of research topics are suggested with the objective of improving equality of opportunity in education and of identifying new policies to improve quality of education in public schools.

Introduction

Differences in educational achievement of students studying at different school types are important for families and governments. Families who select private school option invest a serious portion of their family income in this manner. For example, annual fee of private secondary schools in Turkey varies between 22 to 46 times the monthly minimum salary (Ministry of National Education E-School Portal, 2016).

From the perspective of governments, private school system demands well-founded policy decisions. First, private school system is a resource that enable government to share the burden of the national education services. Moreover, they are considered to possess the capacity to increase the overall quality of educational services. Of course, governments also have to regulate and support the services provided by private schools. In particular, governments often subsidize a group of students, such as students from financially restricted families, so that they can be educated at private schools.

Understanding the effects of school type on the student achievement thus is important as it is the very first step to think further about these individual decision and government policy issues. In this study, the target group is secondary school students and their educational achievements. The specific student achievement measure of this study is the BAS score, which stands for the overall score a student achieves at the end of secondary school that she can utilize during the application to high schools. Ranging from 0 to 500 points, BAS score is an amalgamation of the outcomes of centrally-held examinations and the in-the-classroom performance. Beyond being an indicator of educational achievement, BAS score is a decisive measure in the sense that it shapes the future educational path of students. Several prominent high schools adopt BAS as the central admission criteria (Tebliğler Dergisi, 2013).

Investigation of differences in educational achievement in terms of test scores and/or course grades between public and private school students has long been a prolific and sometimes contested research issue. As Hoxby, Caroline and Murarka (2008) argued, to the layman, it is perhaps surprising that researchers highly struggle to come up with an answer to the narrow question: "What is the effect of private schools on the achievement of students who wish to attend them?".

Abbreviated as "public-private school achievement debate" (Braun, Jenkins, & Grigg, 2006; Peterson & Laudet, 2006), this line of research generally is assumed to start with the study of Coleman et al. (1966). In fact mentioned study was not specifically about public-private debate and its main focus was on reflecting a new perspective on understanding the factors leading to student achievement. Until that date, student achievement was considered to the greater extent an outcome of the quality of the school, which is a function of school resources (Center on Education Policy, 2007). Coleman et al. (1966) controlled for family background characteristics in addition to indicators of schools resources such as expenditures per student, quality of teachers, class size, variety of school facilities, etc. As a striking finding of this pioneering observational study on the student achievement, authors discovered that impact of the size or the variety of resources of the schools on the educational achievement of the students to be minor at best; while the major role was played by the family.

Another important study that scrutinized the educational achievement is provided by Bourdieu (1986) in the sociology field. Emphasizing the close relationship between social background and educational achievement, the author identifies components of the social background as family resources, education levels and occupations of parents, raising up and living in rural or urban areas, and the gender of the student. In this context, social background inherited from the family is the fundamental factor that affects decisions and outcomes related to educational achievement, graduation (or not graduation) from certain schools, studying at rural or urban regions (Bourdieu, 2013). Moreover, social background helps them to do the right thing at the right time in their field and also guide them so that they sense and due prepare for the direction that society tends to incline (Swartz, 2013, p. 11). Bourdieu calls them as *born in the game*, i.e. who are acquainted to the game since they were born (Bourdieu, 2013, p. 73). Bourdieu, Passeron, & Jean-Claude (2014, p. 16-17, 30-31), in Successors, have studied the university students according to their social background. Social background was analyzed in terms of father's occupation, and outcomes such as the likelihood of continuing university education, educational achievements, and artistic activities are compared between representatives of various different social backgrounds. Findings indicate a strong association between education and social background. It was found that the likelihood of a child whose father is a top level manager to enter into university is 80 times greater than a child whose father is a farm laborer (Cansız, 2016, p. 85). In sum, according to Bourdieu (2013), social background poses a very significant effect on both the decisions and the outcomes throughout the educational life, especially at the critical junctions of it.

The main subject of this study, the private school effect, are identified for the first time by Coleman, Hoffer, and Kilgore (1982), whose findings indicated a positive private school effect even after socioeconomic status and other key background characteristics of students were taken into consideration. Mentioned study was criticized for being a cross-sectional one, i.e. that it involved data at a single point in time. It might be possible that private school students were already superior in performance before they got into the private school. So the reason for the differential performance was due to this difference in prior-characteristics rather than due a private school effect (Center on Education Policy, 2007).

In order to address mentioned criticisms, Coleman and Hoffer (1987) conducted a longitudinal analysis that involved tracing students throughout 10th to 12th grade and they monitored their performance trajectory. Findings of the study also indicated a positive private school effect: private school students enjoyed greater performance growth. According to authors, private school students succeeded more number of courses, did more homework, attend more classes and confronts lower number of disciplinary hurdles at the school as compared to the public school students with analogous educational achievement in the previous education levels and with comparable social backgrounds.

Chubb, John, and Terry Moe (1990) integrated data of organizational characteristics of the schools to the Coleman and Hoffer (1987) dataset and found that private school advantage was present and it was associated with much lower numbers of bureaucratic challenges, as well as greater degree of autonomy within private schools. The study found quality of education is not related to teacher salaries, per-pupil spending, or student-teacher ratios. Most significant causes of student achievement were student ability, school organization, and family background, respectively. Bryk, Lee and Holland (1993) studied Catholic schools, which are among prominent private schools in United States, and also found a positive private school advantage, which authors associated to a more coherent academic and social circumstances in that type of schools.

In the study of Center on Education Policy (2007), private school advantage was found to be vanished when supportiveness level of actions and attitudes of parents towards school tasks and issues of their children were addressed in the analysis. Findings indicated that greater proportion of parents whose children were enrolled at private schools possessed characteristics that allows them be more supportive to their children learning challenges. Authors claim that actually this is the reason for the educational achievement gap between the two groups. These parents also carry more ambitious expectations in terms of the educational prospects of their children. Their likelihood of working through the homework with their children is higher. Hence their children receive greater overall support and interactive time from their parents. Those parents are also found to be providing more cultural capital to their children. For example, they go more often to the museums, science-parks or theatres with their parents and more likely to learn to play a music instrument. So, they find ample opportunities to observe and socialize, which create occasions for them to relate what they learn at class to real life experiences as well as urge them to elaborate on these with their parents and friends.

Varied findings are reported about the effects of school type on student achievement. Center of Education Policy (2007) and Abdulkadiroğlu et al. (2009) did not find statistically significant impact, but Angrist et al. (2011) found that studying at a private school has increased math scores by 0.2 standard deviations. Frenette and Chan (2015) also found 8% increase for private school students. On the other hand Chingos and West (2015) ended up with a slightly negative effect of 0.041 standard deviations.

In the context of the studies carried out in Turkey, Berberoğlu, Giray and Kalender (2005) aimed to identify how the academic achievement vary according to different school types and geographical regions. Apart from a few prestigious public high-schools, the achievement difference was found to be the largest among OECD countries. The achievement differences related to living in different regions were comparatively smaller. Alacacı and Erbaş (2010) utilized PISA 2006 study, which includes 4942 students from Turkey in order to study the level of inequality among schools and found that the achievement levels of Turkish schools represent the largest variation among OECD countries. Sulku and Abdioğlu (2015) utilized TIMMS 2011 data to evaluate the factors affecting achievement for primary schools students and found that the average mathematics score of public school students was 446.6 compared to the private schools students' average of 607 after controlling for several background characteristics. Borkan and Bakis (2016) utilized the data of 184.587 secondary-school students to investigate the role of school and student factors for academic achievement. Authors concluded that 18 per cent of the variation was due to intra-school differences whereas the remaining variation was due to within-school factors. However, mentioned study did not use a school type variable, which indexes public and private schools separately.

Reçber, Işıksal, and Koç (2018) investigated if the achievement in mathematics of and the student attitude towards mathematics differ between public and private schools found that levels of achievement did not differ significantly but private school students' attitudes are more positive. Mentioned study faced some data limitations since only 13 school in the district city Ankara were sampled and sampling was not random since the authors selected the schools which are most suited to authors' easy of access. Arslan, Satıcı, & Kuru (2006) evaluated the effectiveness of private and public schools based on the perceptions of teachers by using data consisting 190 teachers from 3 private and 3 public schools in Gebze-Kocaeli in Turkey and concluded that private schools were more effective in terms of the following five criteria: school inputs, school atmosphere, school infrastructure, teaching/learning processes, and the outcomes of this processes. Mohammadi, Akkoyunlu Pınar, and Şeker (2011) investigated the factors important for the students with highest levels of achievement by utilizing a sample of 810 students, found that the type of school played a significant role however the family factors such as the level of education and income of parents did not play a significant role for his particular group of students. A limitation for this study was that it only included schools from Istanbul and the sampling was not random.

On the other hand, our study has a significant advantage of covering the whole student population of secondary school students, which covers over 3.7 million students. The opportunity to utilize the whole population data prevents from representability and sampling related problems and ensures statistical power. In observational studies, the most critical role is played by the study design in order to achieve robust inferences (Imbens & Rubin, 2015; Sekhon, 2007). In this context, the other objective of this study is to present the methodological approach which ensures the robustness of the findings. Robustness requires the exposition of the assumptions foreseen the methodology fully as well as providing the rationale that they are met by the data availability and the effectiveness of the study design. In overall, it is observed that previous studies have not put sufficient emphasis on elaboration of the validity of assumptions and on assessment of robustness of the results. Our study aims to account for the validity of the assumptions and robustness. In addition, this study takes a different stance than the previous studies in Turkey by its focus on an approach, which aims to isolate the causal effect of a unique policy variable, which is here the school type. If we do not isolate the causal effect of a policy variable, then the policies derived from findings of our study would impose risks of being irrelevant or ineffective. In this context, our study also aims to establish an example for implementation of casual inference approach and techniques for the field of education policy research in Turkey. In this context, the implementation of three casual inference techniques -regression adjustment, inverse probability weighting, and exact matching- in a complementary approach is also a contribution of this study to the implementation of causal inference.

On the other hand, the prominent aspect of observational studies is the use of control variables in order to eliminate the bias in estimates, so which control variables to involve is a core question of the observational study design. Findings of the previous literature provide important indications for this purpose. The findings of Bourdieu (2013), Bryk et al. (1993), Coleman et al. (1966) and Center on Education Policy (2007) provide examples from this perspective. There are numerous studies conducted in Turkey as well. In this context, Arı (2007), Sarıer (2010), Şengönül (2013) and Yavuz, Odabaş, and Özdemir (2016) draw attention to the relation between the academic achievement and socioeconomic status. Findings of OECD (2010) indicated that Turkey was in the third rank in OCED member countries according to the interdependency between academic achievement and socioeconomic status. According to Kalaycıoğlu, Çelik, Çelen and Türkyılmaz (2010), socioeconomic status of a household depends on level of education of family members, average monthly income, occupations and workplaces, home or automobile ownership, and means and facilities at the home.

Şengönül (2013) draw attention to two theories and their implementations in term of the relation between socioeconomic status and academic achievement: Family Stress Model and Family Investment Model. According to Family Stress Model (Conger et al., 2002), as a result of the low levels of income relations between family members deteriorate, parents show less interest on their children and exhibit demoralizing behavior which results in provision of little to no help in their educational process. From the perspective of Family Investment Model (Brooks-Gunn, Klebanov, & Liaw, 1995), families with more income provide more financial, social and cultural capital to their children. Findings of İmamoğlu (1987) and Kağıtçıbaşı and Ataca (2005) from Turkey can be regarded as examples in the context of Family Stress Model (Şengönül, 2013). Highlights from mentioned studies indicated that poor parents show less interest in their children's education life, and while they expect gratitude from their children wealthy parents expect less gratitude and provide more autonomy to their children. Examples for Family Investment Model (Şengönül, 2013) involve Ataman and Epir (1972), and Yağmurlu, Çıtlak, and Leyendecker (2009). Major findings of these studies indicate that the role of parents is important;

especially the mother's use of a limited vocabulary and excessive punishment action on the children have implications in terms of academic achievement of the child. Other factors in this context include less amount of education materials procured by the parents, less attention per child in the crowded families and the lower attention of the child during dealing with homework because of the crowded home atmosphere as a result of high number of siblings in large families.

In their study focusing on students of a primary school located in a lower socioeconomic status, Yelgün and Karaman (2015) found that the major factors reducing academic achievement are low education levels of parents, low levels of family income, lack of separate room or study environment of the child, mandatory outdoor working of the children because of lack of adequate income, working of the father in another province, lack of father's regular job and income, and high number of siblings. On the other hand, the fact that the district of the family is located far away from the city center or at a rural area, and the lack of role models in the district are determined in terms of environmental factors affecting academic achievement. Engin-Demir (2009) found the most important factors as the level of education of the father, family's ownership of the home, and teacher-to-student ratio. According to Güvendir (2014) on the other hand factors affecting Turkish skills are gender of the student, level of education of the father, number of books owned, time allocated to reading, receiving private tutoring, the ratio of girls in the school, average size of the class and the location of the school.

Yayan and Berberoğlu (2004) and Ceylan and Berberoğlu (2007) found by using TIMMS 1999 data that the factors affecting science and mathematics achievement are the perception of the student of success and failure, socioeconomic status of the family, education levels of the parents, and student-centered activities. Avşar and Yalçın (2015), based on PISA 2009 data found that students whose fathers have graduate degrees had better reading skills. Moreover, they also observed that children who received pre-school education also had improved reading skills, and they suggested that sending the children to a pre-school is a function of high-enough income levels and the fact that the mother was working. In terms of other studies utilizing PISA 2009 data, Gürsakal (2012) found that gender, age, and education levels of parents are the factors that significantly associated with science and mathematics literacy; and Özdemir and Gelbal (2014) found that socioeconomic status of the family and amenities to study at home are important for academic achievement. Koğar (2015), using PISA 2012 data (OECD, 2010), identified that the factors that affect mathematics literacy are socioeconomic status of the family, gender of the student and the time allocated to learn mathematics. Özbay (2015) is another study utilizing PISA 2012 data to find that the geographical region is an important factor for academic achievement.

The prominent aspect of above-mentioned studies is the fact that the type of the school (public/private) in not controlled for when assessing the relation between several background factors and the academic achievement. One of the contributions of our study is to control for this important aspect.

On the other hand, studies on differences between private and public schools regarding educational achievement do not solely involve observational approach. Numerous experimental and quasi-experimental methods have also been employed. However, there are important tradeoffs involved in choosing one empirical approach over another (Ackerman and Egalite, 2015).

Experimental approach is often regarded as the gold standard methodology for identifying causal effect of private schools that hold admission lotteries. In this setting, treatment and control groups are generated by chance. However, lottery-based studies can only occur when demand of applicants is greater the capacity supply of the private school. Experimental studies typically compare students who have won and lost admissions lotteries at popular charter schools. This identification strategy can yield unbiased estimates of the local average treatment effect for oversubscribed schools, yet such studies can potentially suffer from problems of external validity, as oversubscribed charter schools might differ from undersubscribed charters. As a result, it is unsurprising that the vast majority of experimental studies have been conducted in population-dense urban centers (Hoxby & Rockoff, 2004, Abdulkadiroğlu et al., 2009; Dobbie & Fryer, 2011).

Similarly, in quasi-experimental studies, reliable and valid instruments are hard to find, particularly in large-scale evaluations of charters across multiple locales. Observational studies, meanwhile, permit the researcher to include most charter students in a region, thereby enhancing their external validity. Yet these studies may have weak internal validity because of the challenges associated with establishing an appropriate counterfactual (Abdulkadiroglu et al, 2009).

Peterson and Laudet (2006) argues that there is a pool evidence that well-implemented observational methods can produce unbiased estimates of charter effects, even in the absence of random assignment. Abdulkadiroğlu et al. (2009), Angrist et al. (2011), , and Fortson, Verbitsky-Savitz, Kopa, and Gleason (2012) compare impact estimates generated from experimental data to those from alternative, non-experimental methods to judge how close the estimates produced by an observational approach come to replicating the unbiased experimental estimates. All three studies report promising findings supporting the validity of observational methods for estimating charter effectiveness.

Hence our specific research question is as such: *What is the average causal effect on the BAS score of studying at a private school compared to studying at a public school for secondary school students in Turkey?*

This study attempts not to be restricted to building a predictive model to predict a BAS score conditional on some set of characteristics related to the student and other relevant factors; instead the main objective is to identify the average causal effect of studying at private schools compared to studying at public schools as precisely as possible under a set of appropriate assumptions. Hence the study will set out with setting the framework of causal inference. In the following, theoretical foundations of three different methods that based on *potential outcomes framework* will be introduced. As precision of any causal inference effort is bounded with the appropriateness of the assumptions and limitations of data, detailed account for assumptions and limitations is presented afterwards. Three main causal inference approaches -regression adjustment, inverse probability weighting, and exact matching- will be employed in a manner supplementing each other to estimate the causal effect as robust as possible.

The types of estimators estimated in the analysis section are Average Treatment Effect (ATE), Average Treatment Effect on Treated (ATET), and Potential Outcome Means (POMs) related to ATE and ATET. After the theoretical background on causal inference is set forth, mentioned estimators will be defined in detail and interpreted in the light of findings.

Method

This study aims to estimate the causal effects of school type on the student achievement. Schools type involves two categories: public schools and private schools; whereas student achievement is defined in terms of an overall measure named BAS score (Basis for admission score), which is a weighted score reflecting both the grades obtained from courses in each school and the points obtained at nation-wide centralized exams. Factors used as controls in the study include gender of the student, parental attributes (are they alive and live together; their levels of education and occupations), type of the house, separate room of the student, city the family lives in and its level of development. Study utilizes a dataset comprising 3,752,374 secondary school students, which covers all of the student population within 2014-2016 period. This comprehensive dataset is utilized for the first time. In the context of the below subsections, first the aspects of the dataset is summarized, then casual estimation and its notation, which form the theoretical background of the methodology is set forward. Following section estimation methods are introduced.

Data

This study relies on the administrative dataset provided by the Ministry of National Education of Turkey. Mentioned dataset includes information about the BAS Score and the School Type of all of the 3,752,374 students dispersed over the years between 2014 and 2016. Dataset also includes information about covariates listed at Table-1. As you can see, nearly of the covariates are subjected to no-response to some extent; but generally the ratio of response is substantially higher. Overall we can assert that we are utilizing a close-to-population level of data in our analysis.

Table 1. Data Summary

Variable	Variable Type	Values	Response	No Response
YEP Score	Outcome	Continuous in points	3,752,374	0
School Type	Treatment	Public, Private	3,752,374	0
Gender of Student	Covariate	Boy, Girl	3,751,394	980
Father's Life Status	Covariate	Alive, Not Alive	3,733,213	19.161
Mother's Life Status	Covariate	Alive, Not Alive	3,727,549	24.825
Parent's Marital Status	Covariate	Married, Divorced	3,752,374	0
Father's Education	Covariate	Up to Primary, Secondary/High, Undergrad, Master/PhD	3,219,580	532.794
Mother's Education	Covariate	Up to Primary, Secondary/High, Undergrad, Master/PhD	3,205,073	547.301
Father's Occupation	Covariate	Not Working, Non-Public Worker, Public Worker	3,231,778	502.596
Mother's Occupation	Covariate	Not Working, Non-Public Worker, Public Worker	3,209,181	543.193
Resident Type of Family	Covariate	Rent, Own House, Public Quarter	3,557,865	194.509
Student's Own Room	Covariate	No Own Room, Own Room	3,559,774	192.6
City	Covariate	81 different cities in Turkey	3,748,878	3.496
Year	Covariate	2014, 2015, 2016	3,752,374	0

BAS score is a continuous variable varying between 0 and 504.44 points. Its mean is 294.07 and standard deviation is 100.49. As expected from a standardized test, its Kernel distribution is very similar among the 3-year period taken into consideration in the analysis. Dark blue line represents kernel density of public school students and light blue line represents the Kernel density of private school students (Kernel distribution let us present our data without any need for any functional form restrictions or parametric assumptions. It is similar to Histogram often used, but it also allows for continuity whereas histograms do not (Zuccini, 2003). Population level average of the BAS scores of private school students is 424.20 and it is considerably higher than the population level average of BAS scores of public school students, which is 287.85.

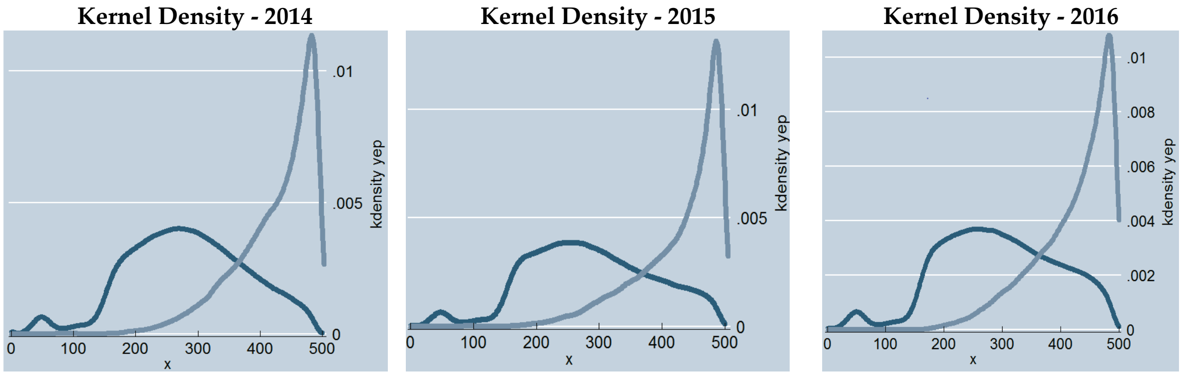

Figure 1. Kernel Densities of BAS Scores for covered period

Causal Inference

This study implements causal inference techniques to identify the average causal effect of studying at private school on educational achievement. Causal inference focuses on comparisons of different treatments applied to the same units; hence it relies on counterfactual interpretations. It differs in this sense from predictive inference, which concentrates on comparisons between different units (Gelman & Hill, 2007). Approaches like Ordinary Least Squares (OLS) that commonly used for predictive inference can also be used for causal inference; but counterfactual interpretation requires substantially stronger assumptions compared to predictive interpretation. Examples of use of OLS based approaches for causal inference are provided in this study. Moreover, several specialized methods have also been developed for causal inference. Regression adjustment estimator, inverse probability weighting estimator and exact matching estimator implemented in this study are examples of such methods.

The most naive estimator for the average effect of private school on educational achievement would involve the straightforward comparison of the average BAS score of private school students and average BAS score of public school students in the population. As we have access to whole population data in terms of individual BAS scores, we can easily do this. But, can we consider this as an unbiased estimate? The answer depends on the answer to a different question: Are these two groups comparable?

One of the core concepts of the causal inference is the treatment status, which is the variable indicating if a certain individual is subject to the intervention or not. For example in this study treatment status is zero for the students enrolled in public schools and is one for the students enrolled in private schools. The group of students whose treatment status is one is named as the treatment group, and group of students whose treatment status is zero is named as the control group. The core objective of randomized studies is obtained balance in distributions of student characteristics between treatment and control groups. When mentioned balance is achieved, two groups would be comparable with respect to their baseline characteristics and would be different only in terms of their treatment status. It is not of any importance if these characteristics were observable or unobservable; or that they were measurable or not measurable; if there are enough number of observations, all those characteristics would be balanced in the two groups.

In contrast, subjects in observational studies, such as in this study, are not necessarily randomly assigned to the treatment group or to the control group, since the researcher has no control over the assignment of the treatment. Hence discrepancies in terms of outcomes of two groups might be partly related to the differences in baseline characteristics if the treatment status is also affected by these baseline characteristics. In that case, participants would self-select themselves into the specific treatment status favored by their characteristics. This *self-selection bias* can be severe.

Baseline characteristics emphasized above, which both affect the level of the outcome variable and the status of treatment variable are named as confounding covariates. If unadjusted for, confounding variables lead to biased estimates of the treatment of interest. Besides, if there is no correlation between the treatment and the suggested confounder or there is no correlation between the outcome and the suggested confounder, then the variable is not a confounder because there will be no bias. If a variable is not a confounding variable, then we need not to take it into consideration that variable in the causal inference context. Concern about R^2 are also at most secondary here because we are not interested in explaining the dependent variable as much as possible. What we are interested in essence is to isolate the causal effect of the treatment variable, to the extent we could.

Observational studies aim to deliver comparable groups that are valid under a set of identifying assumptions. As we will discuss in the following section, one of those assumptions suggests that the treatment can be regarded as almost randomly assigned after conditioning on the set of all confounding observable variables. This is not directly testable as it implicitly suggest that there are no remaining unobservable confounders as well. Hence the findings based on the explicit part of the assumption need to be substantiated by the convincing deliberations of the researcher on the implicit part of the assumption.

Potential Outcomes Framework

Potential outcome notation suggested by Rubin (1974) provides the building blocks for causal inference. Denote D as the indicator of treatment assignment, it is equal to 1 if for treated individuals and is equal to 0 for the individuals in the control group. Let us define Y_{0i} and Y_{1i} for individual i as the potential outcomes. These represent counterfactuals for individual i: Y_{0i} is the outcome if the individual were to receive the treatment and Y_{1i} is the outcome if the individual were not to receive the treatment. The difference between these two potential outcomes would be equal to the causal effect of treatment on individual i. However, we can observe only one of these potential outcomes; we observe Y_{1i} if the individual i is treated or Y_{0i} if the individual i is not treated. In Holland (1986)'s words, this is the fundamental problem of causal inference. So we can also consider causal inference as a challenge related to a missing data problem. Potential outcome framework do not solve this missing data problem at the individual level, but paves the way for conducting causal inference at the distribution level.

Let Y_0 be the vector of potential outcomes in the absence of treatment of all individuals that we are interested with and let Y_1 be their vector of potential outcomes under the treatment. The distribution of Y_0 is the hypothetical distribution of outcome if all individuals were not treated, and distribution of Y_1 is the hypothetical distribution of outcome if all individuals were treated. In this potential outcomes framework, average causal effect η is defined as:

$$\eta = E(Y_1) - E(Y_0)$$

Potential outcomes framework enables formalization of η, and hence makes possible to produce causal statements by the utilization of observational data. What we actually observe is the outcome Y, D and **X**. Here **X** is the vector of covariates that logically and temporally proceed the treatment assignment and hence are not influenced by the treatment assignment. However, we need to identify $E(Y_1)$ and $E(Y_0)$ to identify η. As the first step, we relate the observed outcome Y to counterfactual potential outcomes Y_0 and Y_1 as below:

$$Y = Y(D) = D \cdot Y_1 + (1- D) \cdot Y_0 = \begin{cases} Y_0 & \text{if } D = 0 \\ Y_1 & \text{if } D = 1 \end{cases} \quad (1)$$

We also observe the average outcome level in the treatment and control groups in the sample, which are $E(Y|D=1)$ and $E(Y|D=0)$, respectively. From (1) we can conclude that $E(Y|D=1)=E(Y_1|D=1)$ and $E(Y|D=0)=E(Y_0|D=0)$. However, these are not the same with what we need to know, i.e. $E(Y_1)$ and $E(Y_0)$.

By design, randomized controlled trials manipulates treatment assignment D to make it random. So we can conclude for such studies that $(Y_0, Y_1) \perp\!\!\!\perp D$; i.e. potential outcomes are statistically independent from treatment assignment. In this case $E(Y_1|D=1)$ becomes equal to $E(Y_1)$, and $E(Y_0|D=0)$ becomes equal to $E(Y_0)$. This means that we can use the sample average of treatment group and the sample average of the control group to identify the average treatment effect; taking directly their difference is sufficient.

In an observational study, on the other hand, because the researcher cannot manipulate the treatment assignment D to make it random, we cannot guarantee that potential outcomes are statistically independent of the treatment assignment. In they are not, $E(Y_1|D = 1) \neq E(Y_1)$ and $E(Y_0|D = 0) \neq E(Y_0)$ will hold, which means we cannot use sample averages of two groups for estimating η. Hence, we would need further identifying assumptions, which are discussed in the following section.

Identifying Assumptions

Rosenbaum and Rubin (1983) suggest that conditional on X, we can assume potential outcomes to be statistically independent from treatment assignment, i.e. $(Y_0,Y_1) \perp\!\!\!\perp D|\mathbf{X}$, if it is true that **X** involves all of the confounding covariates. They call this as *ignorable treatment assignment assumption.* If this assumption is valid for our study at hand, then $E(Y_0)$ and $E(Y_1)$ can be identified from what we observe in the sample as follows:

$$E_x\{E(Y|D = 1, \mathbf{X})\} = E_x\{E(Y_1|D = 1, \mathbf{X})\} = E_x\{E(Y_1|\mathbf{X})\} = E(Y_1) \quad (2)$$

$$E_x\{E(Y|D = 0, \mathbf{X})\} = E_x\{E(Y_0|D = 0, \mathbf{X})\} = E_x\{E(Y_0|\mathbf{X})\} = E(Y_0) \quad (3)$$

For identification we need one more key assumption, known as *overlap assumption,* which ensures that the number of observations in treated and control groups to be nonzero for each **X**=**x**. (Cameron & Trivedi, 2005). Overlap assumption requires that:

$$0 < Pr(T = 1|\mathbf{X} = \mathbf{x}) < 1 \quad \forall\, \mathbf{x}.$$

Main identifying assumption of this study, *strongly ignorable treatment assignment* (Rosenbaum & Rubin, 1983) is the combination of the ignorable treatment assignment assumption and the overlap assumption. Overlap assumption guarantees that $E[Y_1 - Y_0|\mathbf{X}=x]$ is identified for all $\mathbf{X}=x$. Ignorable treatment assignment assumption takes care of the rest as follows:

$$\begin{aligned} \eta(x) &= E(Y_1) - E(Y_0) = E[Y_1|\mathbf{X} = x] - E[Y_0|\mathbf{X} = x] \quad (4) \\ &= E[Y_1|D = 1, \mathbf{X} = x] - E[Y_0|D = 0, \mathbf{X} = x] \\ &= E[Y|D = 1, \mathbf{X} = x] - E[Y|D = 0, \mathbf{X} = x] \end{aligned}$$

$$\eta = E[\eta(x)] = E\{ E[Y|D = 1, \mathbf{X}] - E[Y|D = 0, \mathbf{X}] \} \quad (5)$$

Regression Adjustment

In this section three regression based approaches will be introduced. The first approach implements OLS under the assumption of homogeneous treatment effects. The second approach again implements OLS, but this time under the assumption of heterogeneous treatment effects. The third approach implements Regression Adjustment (RA) estimator based on Cattaneo (2010) and Cattaneo, Drukker, and Holland (2013).

OLS under homogeneous treatment effect assumption assumes that the treatment effect is the same for all individuals irrespective of their other characteristics.

As shown in the previous section: $\eta = E\{ E[Y|D = 1, \mathbf{X}] - E[Y|D = 0, \mathbf{X}] \}$

Suppose that the true model is:

$$Y = \beta_0 + \alpha \cdot D + \mathbf{X}^{\prime}\beta\mathbf{X} + \boldsymbol{\varepsilon}$$

$$E(Y|D, \mathbf{X}) = \beta_0 + \alpha \cdot D + \mathbf{X}^{\prime}\beta\mathbf{X}$$

$$E(Y|D=1, \mathbf{X}) - E(Y|D=0, \mathbf{X}) = \beta_0 + \alpha\ (1) + \mathbf{X}^{\prime}\beta\mathbf{X} - \beta_0 - \alpha\ (0) - \mathbf{X}^{\prime}\beta\mathbf{X} = \alpha$$

$$\eta = E\{E(Y|D=1, \mathbf{X}) - E(Y|D=0, \mathbf{X})\} = E\{\alpha\} = \alpha$$

Thus we can estimate η directly by fitting above OLS model.

OLS under heterogeneous treatment effect assumption assumes implicitly that the difference in the treatment effect can differentiate among individuals based on their differentiated characteristics. In order to handle heterogeneous effects, our model needs to also involve the interaction terms between the treatment variable and each of the confounding covariates. Suppose that the true model involving mentioned interaction terms is:

$$E(Y|D, \mathbf{X}) = \beta_0 + \alpha D + \mathbf{X}^{\prime}\beta\mathbf{X} + D\mathbf{X}^{\prime}\psi$$

$$E(Y|D=1, \mathbf{X}) - E(Y|D=0, \mathbf{X}) = \beta_0 + \alpha\ (1) + \mathbf{X}^{\prime}\beta\mathbf{X} + (1)\mathbf{X}^{\prime}\psi - \beta_0 - \alpha\ (0) - \mathbf{X}^{\prime}\beta\mathbf{X} - (0)\mathbf{X}^{\prime}\psi = \alpha + \mathbf{X}^{\prime}\psi$$

So $\eta = E\ \{E(Y|D=1, \mathbf{X}) - E(Y|D=0, \mathbf{X})\} = E\ \{\ \beta_0 + \mathbf{X}^{\prime}\psi\ \} = \alpha + \mathbf{X}^{\prime}\psi$

As seen, we can obtain an estimate of causal effect by estimating the above model as it will provide estimates of α and ψ in addition to **X,** which is already observed.

The final approach in this section implements regression adjustment estimator based on Cattaneo (2010) and Cattaneo et al. (2013). It differs from OLS based estimators described above in two aspects: It is an exactly identified generalized method of moments (GMM) estimator and involves two steps: In the first step, separate linear regression models are fitted with the observed data for the each treatment group, while controlling for the set of confounding covariates.

We have shown that before:

$$\begin{aligned} \eta\ (x) &= E(Y_1) - E(Y_0) = E[Y_1|\mathbf{X} = x] - E[Y_0|\mathbf{X} = x] = E[Y_1|D = 1, \mathbf{X} = x] - E[Y_0|D = 0, \mathbf{X} = x] \\ &= E[Y|D = 1, \mathbf{X} = x] - E[Y|D = 0, \mathbf{X} = x] \end{aligned}$$

First step of RA estimator produces $E[Y|D = 1, \mathbf{X}]$ and $E[Y|D = 0, \mathbf{X}]$ as first corresponds to the line for the fitted values of the regression of outcome on **X** for D=1; and the latter corresponds to the line for the fitted values of the regression of outcome on **X** for D=0. $E[Y|D = 1, \mathbf{X}]$ informs us on $E[Y|D = 1, \mathbf{X} = x]$ for all x, and $E[Y|D = 0, \mathbf{X}]$ also informs us on $E[Y|D = 0, \mathbf{X} = x]$ for all x.

Second step differentiates the above two expectations for each X=x and then averages out for all x as we shown before to estimate ATE:

$$\eta = E_{\mathbf{x}}[\eta(x)] = E_{\mathbf{x}}\{\, E[Y \mid D = 1, \mathbf{X}=x] - E[Y \mid D = 0, \mathbf{X}=x] \,\}$$

Inverse Probability Weighting

Propensity score constitutes the fundamental concept of IPW estimator. The propensity score is defined as the probability of selection into treatment conditional on some set of observed covariates:

$$e(X) = \Pr(D=1 \mid \mathbf{X})=E[D \mid \mathbf{X}]$$

Rosenbaum and Rubin (1983) have shown that if ignorability of treatment assignment assumption holds given **X**, then ignorability of treatment assignment assumption would also hold given propensity score e(**X**). Proof can be found in Imbens (2004, p. 8).

$$(Y_0,Y_1) \perp\!\!\!\perp D \mid e(\mathbf{X})$$

IPW method assigns weights to the individuals by using as weights the inverse of the propensity score, i.e. the probability of being in the observed treatment group in order to make treatment assignment independent of covariates that we condition on.

If we remember from previous sections, causal effect, i.e. average treatment effect is:

$$\eta = E(Y_1) - E(Y_0)$$

Below equations show how IPW estimator identifies η:

$$E[Y_1] = E[E(Y_1|X)] = E\left[\frac{e(X)\cdot E(Y_1|X)}{e(X)}\right]= E\left[\frac{E(D|X)\cdot E(Y_1|X)}{e(X)}\right]= E\left[E\left[\frac{D\cdot Y_1}{e(X)}\right]|X\right]= E\left[\frac{D\cdot Y_1}{e(X)}\right]= E\left[\frac{D\cdot Y}{e(X)}\right]$$

$$E[Y_0]=E[E(Y_0|X)]=E\left[\frac{(1-e(X))\cdot E(Y_0|X)}{1-e(X)}\right]=E\left[\frac{E(1-D|X)\cdot E(Y_0|X)}{1-e(X)}\right]=E\left[E\left[\frac{(1-D)\cdot Y_0}{1-e(X)}\right]|X\right]=E\left[\frac{(1-D)\cdot Y_0}{1-e(X)}\right]= E\left[\frac{(1-D)\cdot Y}{1-e(X)}\right]$$

As $\eta = E[Y1] - E[Y0] = E[Y(1) - Y(0)]$; above two equations together imply:

$$\eta = E\left[\frac{D\cdot Y}{e(\mathbf{X})} - \frac{(1-D)\cdot Y}{1-e(\mathbf{X})}\right]$$

Estimator given below enables us to infer from our data (Horvitz & Thomson, 1952):

$$\tilde{\eta} = \frac{1}{N}\sum_{i=0}^{N}\left[\frac{D_i\cdot Y_i}{e(\mathbf{X}_i)} - \frac{(1-D_i)\cdot Y_i}{1-e(\mathbf{X}_i)}\right]$$

As **e(·)** above stands for the true propensity score and is rarely known, we often need to use estimated propensity score ê(·) (Imbens, 2004**)**. Hirano, Imbens, and Ridder (2003) have shown that use of estimated propensity score is even better than using true propensity score in terms of large sample efficiency. Based on the estimated propensity score, $\hat{e}(X_i)$, we end up with the inverse probability weighting estimator as below (Imbens, 2004):

$$\tilde{\eta} = \sum_{i=0}^{N}\frac{D_i\cdot Y_i}{\hat{e}(X_i)} \Big/ \sum_{i=0}^{N}\frac{D_i}{\hat{e}(X_i)} - \sum_{i=0}^{N}\frac{(1-D_i)\cdot Y_i}{1-\hat{e}(X_i)} \Big/ \sum_{i=0}^{N}\frac{D_i}{1-\hat{e}(X_i)}$$

Matching

Matching is a nonparametric method that at first constructs a matched group for the treated group based on the similarities in terms of confounding characteristics, and then compare their average outcomes at the second step (Rosenbaum & Rubin, 1983; Ho, Imai, King, &.Stuart 2007). Exact matching estimator $\tilde{\eta}$ employed in this study is such that (King & Nielsen, 2016, p. 4):

$$\tilde{\eta} = \text{mean}_{i\in\{i \mid D_i=1\}}[Y_i-\hat{Y}_i(D=0)] \qquad \text{where } \hat{Y}_i(D=0) = \text{mean}_{j\in\{j \mid X_j=X_i, D_i=1, D_j=0\}}\, Y_j$$

given $E[Y_0 \mid X=x] = E[Y_0 \mid D=0, X=x] = E[Y \mid D=0, X=x]$ under strong ignorability;

$$E(\tilde{\eta}) = \eta$$

Results

Assessment of Confounding Covariates

As mentioned in the section titled *Data*, population level average of the BAS scores of private school students is 424.20 and it is considerably higher than the population level average of BAS scores of public school students, which is 287.85.

If the treatment assignment could be considered as random and independent from the potential outcomes, as in randomized experiment studies, the treatment and control groups would be balanced in terms of other important characteristics. In this case we can use the difference between average outcome levels of treatment and control variables as the estimator for population level average treatment effect since the only different characteristic remained between the two groups that we can attribute the effect on outcome is the school type. So in that case, 424.20-287.85 = 136.35 points would be the population level average treatment effect, which is quite sizeable.

As this study is an observational one instead of a randomized experiment, assignment mechanism is not necessarily random. Because of self-selection into treatment, other important characteristics may not be balanced, which can potentially bias our estimates. Imbens and Rubin (2007) suggest the use of normalized difference for each covariate to assess the imbalance between treatment and control groups.

Normalized difference = $\frac{\bar{X}(D=1)-\bar{X}(D=0)}{\sqrt{S^2(D=0)+S^2(D=1)}}$ ($S^2(D=w)$ is the sample variance for group w)

We can observe from Table-2 that indeed several covariates are indeed unbalanced as normalized difference is far from being equal to zero; for some variables it is even around one. This is an indicator for sizeable levels of bias introducing self-selection, which we need to correct for.

Table 2. Comparison of Covariate Values among the Treated and Control Samples

Covariates	$\bar{X}$(D=1)	S(D=1)	$\bar{X}$(D=0)	S(D=0)	Normalized Difference
Gender of Student	0.462	0.499	0.483	0.5	-0.030
Father's Life Status	0.015	0.12	0.023	0.149	-0.042
Mother's Life Status	0.003	0.058	0.007	0.82	-0.005
Parent's Marital Status	0.089	0.284	0.081	0.273	0.020
Resident Type of the Family	1.813	0.486	1.693	0.496	0.173
Student's Room at Home	0.904	0.295	0.405	0.491	0.871
Father's Education	2.486	0.676	1.475	0.651	1.077
Mother's Education	2.278	0.759	1.261	0.517	1.107
Father's Occupation	2.469	0.857	2.113	0.616	0.337
Mother's Occupation	1.962	1.136	1.256	0.574	0.555
Development Priority of Home City	1.948	0.222	1.829	0.377	0.272
Geographic Region of the Home City	5.362	1.76	4.491	2.223	0.307
Year	1.167	0.818	0.961	0.808	0.179

If we revisit the criteria for assessment of a confounding covariate; to be employed as a confounding covariate and thus controlled for, a covariate needs to be (Imbens & Rubin, 2015, p. 265-66):

1. A confounding covariate should be correlated with both the outcome variable and the treatment variable at the same time. If there is no correlation between the treatment and the suggested confounder or if there is no correlation between the outcome and the suggested confounder, then the variable is not a confounder because there will be no bias. The degree of this double-correlated is also important; more emphasis shall be put on covariates with higher double-correlation.
2. We should not employ post-treatment variables as confounding covariates. Post-treatment variables are measured after or at same time with the treatment, are themselves affected from the treatment or are consequences of the treatment. We need to be sure that confounding covariates chosen have to be pre-treatment variables, which are logically prior to the treatment and most importantly cannot be affected from the treatment.

In terms of the first condition, correlations between outcome, treatment and potential confounding variables are presented in Table-3. Father's education, mother's education, and existence of student's own room at home are the three potential confounding variables that have highest double-correlation levels. Father's occupation, mother's occupation, geographical region of the school, and development priority of the home city follows them as the second group in terms of double-correlations. Year and resident type of the family constitutes a third group in that sense. These three groups are suitable for being selected as confounding covariates. Father's life status, mother's life status, and parent's marital status are almost not correlated with neither the outcome nor the treatment variable. Gender has a considerable correlation level with the outcome variable but almost have non-existing correlation with the treatment variable, which disqualifies it from being a confounding covariate.

Table 3. Correlations between Outcome, Treatment and Potential Confounding Variables

	YEP Score	School Type	Gender	Father's Life Status	Mother's Life Status	Parent's Marital Status	Father's Education	Mother's Education	Father's Occupation	Mother's Occupation	Resident Type of Family	Student's Own Room	Geographical Region	Development Priority	Year
YEP Score	1.000														
School Type	0.272	1.000													
Gender	0.160	-0.010	1.000												
Father's Life Status	-0.015	-0.009	0.002	1.000											
Mother's Life Status	-0.012	-0.005	0.000	0.017	1.000										
Parents' Marital Status	-0.017	0.007	0.005	0.389	0.134	1.000									
Father's Education	0.444	0.310	0.006	-0.021	-0.011	0.018	1.000								
Mother's Education	0.400	0.366	0.005	-0.016	-0.010	0.076	0.582	1.000							
Father's Occupation	0.283	0.116	0.001	-0.020	-0.006	-0.023	0.485	0.307	1.000						
Mother's Occupation	0.204	0.231	0.000	-0.005	-0.005	0.077	0.288	0.465	0.234	1.000					
Resident Type of Family	0.063	0.050	-0.003	0.001	0.002	-0.059	0.043	0.024	0.055	0.027	1.000				
Student's Own Room	0.334	0.197	0.010	-0.016	-0.010	0.031	0.382	0.373	0.230	0.176	0.067	1.000			
Geographical Region	0.135	0.073	0.002	-0.013	-0.009	0.047	0.107	0.144	0.024	0.057	-0.075	0.217	1.000		
Development Priority	0.155	0.084	0.003	-0.014	-0.010	0.057	0.141	0.184	0.045	0.074	-0.103	0.247	0.807	1.000	
Year	0.051	0.058	-0.002	-0.017	-0.011	-0.029	0.027	0.032	0.003	0.016	-0.012	0.026	0.010	0.011	1.000

Table 4 presents detailed account of distributions of outcome and treatment levels with respect to different values of each covariate. Apart from reflecting the same information of Table-3 in a different and more detailed format, Table 4 provides the perspective of the potential outcome framework for assessment of confounding covariates. As an illustration, let us analyze the case for father's education.

In order to set an example on how to interpret the information in Table-4, detailed explanations will be provided by using father's education covariate. Same style of explanation is also valid for the other covariates. In terms of father's education, ratio of treated students to overall population increases with each incremental increase in education level. Whereas only 0.77% of students whose fathers' education level is up-to primary school are enrolled to a private school, this increases to 4.41% for students whose fathers' education level are secondary and high school level of education, to 21.91% for students whose fathers' education level is undergraduate, and to 42.60% or students whose fathers' education level are masters or PhD. This indicates a strong correlation between the level of education of father and the odds of enrollment of the children to a private school. This is also an evidence for the case that fathers with higher level of education have a significantly higher tendency to enroll their children to a private school. In other words, they self-select their children to a private school at a higher rate as their level of education becomes higher. As discussed before, self-selection like this would mean that the direct comparison of sample means of treated and control groups would lead to bias if father's education level is also correlated with the BAS score.

Another important observation from Table-4 is the fact that BAS score increases with each incremental increase in the level of father's education both for the treated and control groups. In the treated group, average BAS score of private school students whose fathers' level of education is up-to primary is 377.21, this increases to 402.59 for private school students whose fathers' level of education is secondary or high school, to 443.97 for private school students whose fathers' level of education is undergraduate, and to 453.65 for private school students whose fathers' level of education is masters or PhD. In the control group, average BAS score of public school students whose fathers' level of education is up-to primary is 266.26, this increases to 320.19 for public school students whose fathers' level of education is secondary or high school, to 387.32 for public school students whose fathers' level of education is undergraduate, and to 394.74 for public school students whose fathers' level of education is masters or PhD.

Table 4. Distributions of Outcome & Treatment Levels with Respect to Different Values of Covariates

		Population						Treatment: Private School				Control: Public School			
		# of Obs.	% of Obs.	YEP Score		Ratio of Treated	Ratio of Control	# of Obs.	% of Obs.	YEP Score		# of Obs.	% of Obs.	YEP Score	
				Mean	Std.Dev.					Mean	Std.Sap.			Ortalama	Std. Sap.
Gender of Student	Boys	1,943,703	51.80	279.15	99.87	4.73	95.27	91,974	53.75	417.62	70.10	1,851,729	51.71	272.27	96.05
	Girls	1,807,691	48.17	310.16	98.63	4.37	95.63	79,037	46.19	432.02	61.13	1,728,654	48.27	304.60	96.40
	No Response	980	0.03	217.39	109.55	11.84	88.16	116	0.07	321.25	102.02	864	0.02	203.44	102.88
Father's Life Status	Alive	3,650,334	97.28	294.76	100.43	4.60	95.40	167,952	98.14	424.57	66.40	3,482,382	97.24	288.50	97.51
	Not Alive	82,879	2.21	276.03	97.62	2.99	97.01	2,482	1.45	409.04	67.93	80,397	2.24	271.92	95.49
	No Response	19,161	0.51	241.76	102.80	3.62	96.38	693	0.40	389.01	86.95	18,468	0.52	236.24	99.18
Mother's Life Status	Alive	3,702,787	98.68	294.44	100.44	4.57	95.43	169,128	98.83	424.52	66.36	3,522,659	98.67	288.21	97.53
	Not Alive	24,762	0.66	265.07	97.92	2.31	97.69	571	0.33	407.90	72.93	24,191	0.68	261.70	95.90
	No Response	24,825	0.66	268.01	101.81	5.75	94.25	1,428	0.83	393.10	79.54	23,397	0.66	260.38	97.98
Parents' Marital Status	Married	3,445,708	91.83	295.34	100.43	0.45	99.55	155,973	91.14	425.90	65.47	3,289,735	91.86	289.15	97.54
	Divorced	306,666	8.17	279.80	100.04	4.94	95.06	15,154	8.86	406.72	74.83	291,512	8.14	273.20	96.73
Resident Type of Family	Rent	1,135,999	30.27	291.27	96.88	3.14	96.86	35,617	20.81	424.35	66.14	1,100,382	30.73	286.96	94.64
	Own House	2,359,709	62.89	296.51	99.35	4.81	95.19	113,502	66.33	422.81	66.10	2,246,207	62.72	290.13	96.44
	Public Quarter	62,157	1.68	364.32	92.36	10.44	89.56	6,489	3.94	447.76	51.27	55,668	1.58	354.59	91.17
	No Response	194,509	5.18	258.35	120.61	7.98	92.02	15,519	9.07	424.16	74.39	178,990	5.00	243.98	112.86
Student's Room at Home	No Own Room	2,039,800	54.36	266.70	93.19	0.74	99.26	15,032	8.78	402.46	75.18	2,024,768	56.54	265.69	92.57
	Own Room	1,519,974	40.51	335.37	92.54	9.30	90.70	141,373	82.61	426.64	64.20	1,378,601	38.49	326.01	89.88
	No Response	192,600	5.13	258.05	120.28	7.64	92.36	14,722	8.60	422.97	75.02	177,878	4.97	244.40	112.96
Father's Education	Up to Primary	1,898,001	50.58	267.11	90.07	0.77	99.23	14,524	8.49	377.21	75.07	1,883,477	52.59	266.26	89.68
	Secondary/High S.	971,183	25.88	323.82	86.99	4.41	95.59	42,819	25.02	402.59	67.71	928,364	25.92	320.19	86.06
	Undergrad	322,816	8.60	399.73	77.18	21.91	78.09	70,713	41.32	443.97	53.01	252,103	7.04	387.32	78.33
	Master/PhD	27,580	0.74	419.84	77.92	42.60	57.40	11,750	6.87	453.65	48.10	15,830	0.44	394.74	85.93
	No Response	532,794	14.20	265.37	108.94	5.88	94.12	31,321	18.30	419.86	72.34	501,473	14.00	255.72	103.44
Mother's Education	Up to Primary	2,406,931	64.14	278.34	91.88	1.09	98.91	26,264	15.35	387.40	74.01	2,380,667	66.48	277.13	91.33
	Secondary/High S.	618,205	16.48	344.88	86.74	7.90	92.10	48,850	28.55	413.30	65.04	569,355	15.90	339.01	85.85
	Undergrad	167,183	4.46	420.63	69.79	35.17	64.83	58,793	34.36	448.58	50.46	108,390	3.03	405.47	74.03
	Master/PhD	12,754	0.34	420.18	81.30	50.27	49.73	6,411	3.75	455.06	47.02	6,343	0.18	384.92	92.64
	No Response	547,301	14.59	264.28	108.68	5.63	94.37	30,809	18.00	419.86	72.33	516,492	14.42	255.00	72.33
Father's Occupation	Not Working	172,960	4.61	246.51	93.39	0.43	99.57	746	0.44	392.18	78.59	172,214	4.81	245.88	92.92
	Non-Public Worker	2,765,515	73.70	293.20	95.26	3.84	96.16	106,110	62.01	418.30	67.35	2,659,405	74.26	288.21	92.77
	Public Worker	293,303	8.48	379.73	85.28	11.32	88.68	33,188	24.06	447.30	51.63	260,115	7.83	371.11	84.88
	No Response	520,596	13.87	266.26	109.15	5.97	94.03	31,083	18.16	420.46	72.08	489,513	13.67	256.47	103.61
Mother's Occupation	Not Working	2,490,394	66.37	292.59	95.38	2.56	97.44	63,864	37.32	408.42	69.46	2,426,530	67.76	289.54	94.06
	Non-Public Job	618,323	16.48	304.47	100.11	7.62	92.38	47,086	27.52	430.36	62.35	571,237	15.95	294.10	95.46
	Public Job	100,464	2.75	419.73	71.31	29.16	70.84	29,297	20.66	452.53	47.37	71,167	2.03	406.23	47.37
	No Response	543,193	14.48	265.78	108.82	5.68	94.32	30,880	18.05	420.58	71.97	512,313	14.31	256.45	103.50
Development Priority of Home City	Level-6 (Highest)	621,814	16.59	241.95	99.79	1.43	98.57	8,913	5.21	403.85	76.10	612,901	17.13	239.60	98.16
	Level-5	347,576	9.27	297.50	96.20	2.64	97.36	9,186	5.37	433.25	61.06	338,390	9.46	293.82	94.29
	Level-4	385,600	10.29	305.78	94.53	3.30	96.70	12,708	7.43	427.13	63.62	372,892	10.42	301.64	92.65
	Level-3	480,665	12.82	297.57	99.44	3.33	96.67	15,994	9.35	430.56	62.80	464,671	12.99	293.00	97.28
	Level-2	534,525	14.26	303.90	98.51	4.37	95.63	23,348	13.64	429.86	64.06	511,177	14.29	298.15	95.93
	Level-1 (Lowest)	1,378,698	36.78	308.64	96.69	7.32	92.68	100,978	59.01	422.49	67.20	1,277,720	35.71	299.65	92.87
Geographic Region of the Home City	Eastern Anatolia	356,494	9.51	266.56	103.05	1.97	98.03	7,017	4.10	421.66	67.12	349,477	9.77	263.45	101.24
	South-Eastern Anat.	548,172	14.62	246.91	100.17	1.81	98.19	9,947	5.81	411.08	74.56	538,225	15.04	243.87	98.03
	Black Sea	339,123	9.05	309.88	92.28	2.58	97.42	8,747	5.11	433.24	60.48	330,376	9.23	306.62	90.72
	Mediterrenian	510,797	13.63	300.60	98.49	3.99	96.01	20,402	11.92	428.66	63.64	490,295	13.70	295.27	96.04
	Central Anatolia	577,004	15.39	311.89	95.57	6.09	93.91	35,112	20.52	423.59	64.94	541,892	15.15	304.62	92.69
	Agean	406,461	10.84	309.04	97.72	5.42	94.58	22,031	12.87	433.00	60.14	384,430	10.75	301.93	94.65
	Marmara	1,010,827	26.96	304.89	97.00	6.71	93.29	67,871	39.66	421.35	69.10	942,956	26.36	296.51	93.26
Year	2014	1,287,988	34.32	289.08	97.26	3.52	96.48	45,307	26.48	424.15	64.83	1,242,681	34.70	284.16	94.67
	2015	1,287,978	34.32	292.12	101.56	4.03	95.97	51,936	30.35	428.60	67.65	1,236,042	34.51	286.39	98.69
	2016	1,176,408	31.35	301.67	102.32	6.28	93.72	73,884	43.17	421.14	66.69	1,102,524	30.79	293.66	99.26

So for both treated and control groups, level of father's education is positively and strongly correlated with the higher BAS scores. For higher levels of father's education, we observe higher average BAS scores in the both groups. However, it's also noticed that the gap in the average BAS score between the two groups does not remain constant for different level of father's education. While the gap is 377.21-266.26=110.95 points for the students whose fathers' level of education is up to primary school, it is 82.40 points for the students whose fathers' level of education is secondary or high school, 56.65 points for the students whose fathers' level of education is undergraduate, and 58.91 points for the students whose fathers' level of education is masters or PhD.

Table-4 also help us assess the level of balance between the treated and control groups for each covariate. If we concentrate on father's education level once again, we observe that the distribution of education levels lack balance between the treated and control groups. While only 8.49% of the students in the treated group have fathers with up to primary school level of education, that figure is 52.59% for the students in the control group who have fathers with up to primary school level of education, so both groups are seriously unbalanced. In terms of the students whose fathers have education level of secondary or high school, mentioned figures are %25.02 of the treated group and %25.92 of the control group. It is noticed that for this level of education, the two groups are almost balanced. Whereas 41.32% of the students in the treated group have fathers with undergraduate level of education, that figure is only 7.04% for the students in the control group who have fathers with undergraduate level of education, so once again both groups are seriously unbalanced. In terms of the students whose fathers have education level of masters or PhD, mentioned figures are %6.87 of the treated group and %0.44 of the control group; so once more there exists certain amount of imbalance at this level of education between the two groups. Consequently, if we compare treatment and control groups in terms of the distribution of the father's education covariate, we observe that two distributions are quite different.

If we consider together the structure of imbalance described above and the fact that BAS score increases as the level of father's education increases, we can understand the source of bias emanating from self-selection. Compared to the control group, higher portion of students in the treated group are concentrated in the higher levels of father's education. As BAS score is increasing in higher education levels of the father, the greater concentration of treated group in the high levels of father's education amplifies the average BAS score of treated group relative to control group. Hence average BAS score difference between the two groups emanates from firstly the causal effect of private school enrollment and secondly the greater concentration of higher levels of father's education within the father's education distribution of private school students.

Interpretation style described above is similarly appropriate for mother's education, father's occupation, mother's occupation and student's own room at home. However in terms of father's occupation, for the observant eye there lies one more caveat. We normally desire precisely categorized categorical variables in our analysis in which sense each category inhabits very similar, tightly defined properties that we can argue them as lying within an acceptable boundary and not overlapping with other categories. Except for father's occupation, categorization of covariates considered in this study could be argued to possess from straightforwardly unequivocal (such as gender) to satisfactory categorization. For father's occupation, there is no overlap between the other category subgroups which are non-working and public-worker as those can be strictly differentiated from non-public worker. However, within non-public worker sub-category there exist several subgroups which could be considered to possess considerably different characteristics. This subgroup involves a very wide spectrum of income types ranging from minimum wage earning workers to very rich businessmen, of expertise and experience ranging from farmers to entrepreneurs of advanced technologies are all fit to this sub-category. Moreover, the size of the sub-category for fathers with 2,765,215 individuals is quite large compared to mother for whom the number is 618,323. At the best case, we would desire to divide this sub-category to at least two sub-groups. That would be much more informative. Unfortunately, we do not have data at that resolution. However, as we can expect a correlation between job status and education level of father, we can explore if this could be informative about what is going on within non-public worker subcategory. In Table-5, left box show the summary of sub-classification done by grouping father's occupation and father's education covariates. The right box presents results for father's education alone. What we observe is that father's education seems to reflect enough the degradation within the subcategory as the distribution of results are quite close in both boxes. So controlling for father's education at the same time with father's occupation and/or adding an interaction term instituting both covariates seems to solve most of the problem.

Table 5. Interplay between of Non-Public Job Status of Father's Occupation and Father's Education

Grouped Covariates		Number of Observations	YEP Score Overall	School Type Private (%)	Covariate	Number of Observations	YEP Score Overall	School Type Private (%)
Father's Occupation	**Father's Education**				**Father's Education**			
Non-Public Job	Up to Primary	1,721,615	**269.39**	**0.81**	Up to Primary	1,898,001	**267.11**	**0.77**
Non-Public Job	Secondary/High Sch.	844,215	**322.29**	**4.60**	Secondary/High Sch.	971,183	**323.82**	**4.41**
Non-Public Job	Undergrad	150,618	**396.02**	**29.52**	Undergrad	322,816	**399.73**	**21.91**
Non-Public Job	Master/PhD	15,882	**414.91**	**47.90**	Master/PhD	27,580	**419.84**	**42.60**

In terms of socio-economic development level of the city in which the student is living in, the average score of 6th level, i.e. the lowest development level, is 241.95 points, whereas the average scores of other five levels are condensed within a narrow interval of 297.50 and 308.64 points. Moreover, there is no solid association between the level increments and average BAS score improvements. For example, while 5th level average is 297.50 points, it rises to 305.84 points for 4th level, but falls back to 297.57 points for 3th level. In terms of the geographical region that the student lives in, Eastern Anatolia with 300.60 points and South-eastern Anatolia with 311.89 points are observed to differentiate from the remaining pile of regions whose average BAS scores are condensed within a narrow interval of 300.60 and 311.89 points. On the other hand, the group of cities whose development level is 6 are same as the cities of East Anatoli and South East Anatolia combined. In this context, outcome only varies considerably between this group of cities and remaining pile of cities. Hence, in order to improve the significance, precision, and degree of freedom of the analysis, it can be considered to form a new variable called City Development Index, which is equal to 1 for the group of least developed cities mentioned above, and is equal 0 for remaining cities.

In terms of resident type of the family, only students whose family lives in public quarters differentiate significantly in terms of BAS score and treatment assignment ratio. Moreover, the imbalance between treated and control groups are not as pronounced as the covariates mentioned above. So it's less confounding and moreover because of less imbalance, confounding does not translate into a problem at the same scale. In terms of gender covariate, girls seem to achieve better BAS scores with around 5% higher in the treated group and 10% higher in the control group. However gender is not much a confounding covariate as the treated ratio is nearly same for both groups (4.73% vs 4.37%) while the two groups are nearly balanced: boys constitute 53.75 in the treated group and 51.71 in the control group, which are very close. For father's life status, mother's life status, and parents' marital status, ratio of treated and BAS scores in treated and control groups vary as the status changes, albeit at a quite smaller size compared to strongly confounding variables mentioned above. However, because of relatively higher balance between treated and control groups, small overall confounding effect could be expected.

Finally, in terms of the second condition for eligibility for being a confounding covariate, we can consider each of the covariates as post-treatment variables. Gender, father's life status, mother's life status, parents' marital status, father's education, mother's education, geographical region or development priority of the home city are unquestionably prior to treatment assignment in logical or time sequence and cannot be affected from the treatment assignment. For resident type of family and existence of student's own room, this argument is not as unquestionable as above-mentioned covariates, as at least a change in a status of each of the two covariates can coincide with the time of the treatment assignment; but in general we can assume that their status is not affected by the treatment decision.

Rationale for Ignorable Treatment Assignment Assumption

As mentioned in the above sections, the core assumption of this study for identification is the ignorable treatment assignment, which requires that there are no remaining unaddressed confounders. Two types of such confounders can threat our analysis. Unobservable confounders is the first type, observable confounders that we could not able to observe because of lack of data is the second type. Randomization (by pure experiment design or by use of an instrumental variable) is the preferred cure for dealing with unobservable confounders, but unfortunately it is out of our reach in this observational study. Next best cure is to find a good proxy. On the other hand, for unobserved observables, the cure is to collect better data. But because of several reasons like cost or practicality, it is not always possible or cost-effective to do so.

Resorting to the previous literature and the institutional knowledge about the field is important first step for thinking about any remaining unobservable and observable-but-unobserved potential confounders. A rich set of covariates analyzed in the previous section covers a large part of the potential confounders mentioned in the previous literature. Family characteristics and spatial factors are listed as prominent confounders in the literature. Almost all of these, which are as a group called as social background by Bourdieu (1986), are covered in this study. Some potential confounders suggested in the previous literature are post-treatment variables, i.e. they do not meet the criteria of not being affected by the treatment, so we shall not take them into consideration. Parental involvement in school activities (Center on Education Policy, 2007) or absenteeism rate (Peterson & Laudet, 2006) are such examples. However, there is one important potential unobservable confounder and one potential observable-but-unobserved confounder suggested in the previous literature that are not controlled for this in this study and deserve to be scrutinized carefully.

The unobservable factor is the child's intrinsic ability and/or motivation for educational achievement. This student characteristic can differ sizably between students who have the same set of observable factors that we have accounted for in the previous section. If by self-selection students with higher ability and/or motivation are disproportionately enrolled into private schools, than this would lead to upward bias in the estimated private school effect since average expected potential outcomes for a group with categorically higher ability and/or motivation would also be higher. In order to account for this factor, the implementation of previous test scores as a proxy are suggested and/or implemented in the previous literature (Alexander & Pallas, 1985; Peterson & Laudet, 2006; Abdulkadiroglu et al., 2009).

The first issue with controlling for a previous test score is its existence; it generally does not exist at the secondary school level. This is the case for this study, but to a large extent it's also the same for referenced studies, too. So, at the secondary school level, this proxy covariate is also unobservable. The second issue with controlling for previous test scores is its requirement; do we really need to control for it, i.e. is self-selection is evident at that extent? In order that self-selection occurs, it shall be the case that at the same time parents are categorically more inclined to enroll their children with higher ability and/or motivation to private schools. As Ackerman and Egalite (2015) argues, this might be valid for some of the parents but the opposite could also happen, i.e. parents of under-performing students may be more inclined to look for an alternative to the traditional public schooling, and this would lead to an underestimation of private school effects. So, bias could go in both ways, somewhat cancelling each other. Confirming this line of argument, Abdulkadiroglu et al. (2009) and Chingos and West (2015, p. 11) both found out that using pre-treatment baseline test score as a proxy in order to control for unobserved ability and/or motivation leads to almost no change in the estimates. Moreover, as inferred from lack any objective of pre-test scores, there are no clear indicators of the relative achievement potential of the child, which makes informed decision by the parents about the two scenarios mentioned above harder. So not-much-informed profile of parents also implies more of a random decision rather than an inclination for self-selection in terms of this unobserved factor. In addition, numerous private schools accept students by conducting lotteries during primary school period in Turkey, which further works against self-selection concerns.

On the other hand, the selection decision circumstances discussed above applies to families that can afford the sizable cost of private schools present in Turkish education system. The studies referenced above are most of the time on charter schools in United States. The cost difference between a public school and charter school, which can be seen as an independently steered and modified version of a public school, is not as exclusivist compared to the cost differential between Turkish public and private schools. Consequence of this is that parents that can't afford private school fees are restricted to *self-unselecting* in Turkey. In other words, their decision is strongly correlated with enrollment to public schools, only exception might be a scholarship opportunity provided to their child. If the children of these families have lower average potential outcomes then this would lead to biased estimates. In line with this line of thinking, Lee and Burkham (2002) argues that students may even begin to kindergarten with different achievement level, but they attribute this mainly to their social class rather than unobserved ability and/or motivation of these children. Bourdieu (1986) also claims that the educational achievement is largely related to the early years of life, and school education is built on this basis. Previous skills and knowledge rooted from family environment have the critical role for receiving, interpreting, and practicing the inputs sent in the school. Lareau and Horvat (1999) discusses that students from lower income families receive fewer educational resources in their home compared to students from higher income families, while at the same time their parents in most of the cases can invest less time for them and possess lower levels of education, which corresponds to less overall support to their children. Consequently, the plausible case that financially-restricted parents mandatorily self-select their children into public schools and plausible case that they might on average provide less educational support in together would lead to bias. However this bias is not a result of differences in intrinsic ability and/or motivation of the child but of differences in social backgrounds. The set of controls described in the previous section, especially parent's education and occupation, as well as existence of an own room at home and the region that student lives in can be considered to address this problem to a satisfactory extent.

On the other hand, the observable-but-unobserved factor is the distance between the home of the student and the school. Based on the certain set of reasons such as travel cost, safety, neighborhood friends, most parents are inclined to send their children at young ages to schools in close proximity to their homes. Hence distance between the child's home and the nearest private school is a determinant of the selection decision of the parents. Parents are more inclined to send their children to a private school if it is close to their home and are less inclined to send if it is far away (Hoxby et al., 2008). In order that this distance is a confounding covariate, it shall also be in correlated with the potential outcomes of the student. Distance of the student's home to a private school can be correlated with student's educational achievement, i.e. BAS score, in the sense that private secondary schools in Turkey generally populate within city centers or take place at outside of the city which is generally far away from all residential areas. For students living at city centers and that have parents allocated with ample financial resources, distance is a much less important factor compared to the students living at the periphery districts or at rural areas. Distance is smaller problem for parents of the former students since at a reasonable location most probably there would be a private school, and the expected support they are to give to their children is not likely to depend on the distance. Majority of parents of the latter students on the other hand are expected to be inclined not to send their children to private schools and at the same time these parents are also expected to be less supportive to their children compared to former parents as the resources they can provide for their children likely to be more restricted than them: they are expected to have earn substantially less income and also have lower educational attainment. This corresponds to lower average potential outcome levels for these students who categorically receive less support. However, these resource-based factors can be regarded to be covered to a satisfactory degree by already controlled observable covariates. Parents' education and occupation coupled with existence of own room and the region student lives in could be considered to largely determine where the student lives and degree of support she receives from their parents. Nonetheless, it is advised that data on location of the home and school of a student, at least at the level of urban, suburban, or rural area, are collected by the Ministry of National Education of Turkey.

Rationale for Using Different Estimation Methods Together

RA, IPW, and matching estimators are all rely on the same strong ignorability of treatment assignment assumption. However RA estimators and IPW estimators also rely on additional modelling assumptions, while this does not apply to exact matching estimator because of its non-parametric nature. RA and IPW estimators also differ by their modelling assumptions. RA estimators rely on functional form assumptions solely to model the outcome. They do not necessitate any assumptions on the functional form for the probability of treatment model. In contrast, IPW estimators rely on functional form assumptions only to model the probability of treatment. They do not need any assumptions about the functional form for the outcome model. On the other hand, doubly-robust estimators can be implemented by using these two methods in conjunction. Doubly-robust models require that only one of the models is correct. It is enough to correctly fit either the outcome model or the treatment assignment model. This is an important property, which improves the robustness of our estimates (Robins & Rotnitzky, 1995; Imbens 2004; Luncefort & Davidian, 2004; Imbens & Wooldridge 2009; Cattaneo et al., 2013; Stata Corp, 2015a, 2015b; Wooldridge, 2010).

If the covariate distributions are seriously unbalanced between the treatment and control groups, conventional regression methods like OLS might be vulnerable even to small variations the functional form specification because of their heavy reliance on extrapolation (Imbens, 2015). We can infer from Imbens and Rubin (2007) that normalized difference of more than 0.25 stands for a sizable level of unbalance. As we have observed in the previous sections, there are variables with normalized difference even over 1.00, hence relying solely on regression adjustment estimates would be questionable in terms of robustness. Hence implementation of other complementary approaches are due implemented.

One advantage of RA estimator is such that when the overlap assumption is on the verge of being violated, there exist very low number of treated observations for certain covariate combinations, so RA estimators resort to the model to make predictions at regions harboring scarce amount of data. Other two approaches are not helpful in terms of these regions.

On the other hand, IPW estimators are sensitive with respect to overlap assumption. They start to produce erratic estimates as the overlap assumption gets close to being violated. If that happens, certain subsets of the inverse-probability weights inflate and the large-sample distribution no longer qualifies as a sufficient approximation to the finite-sample distribution of IPW estimators. This erratic behavior persists even in the case of correct specification of the functional form for the treatment model is ensured. However, with correct model specification and enough number of observations, RA estimator does not start to exhibit such an erratic behavior as fast as the IPW estimator, and its large-sample distribution still qualifies as a sufficient approximation to the finite-sample distribution (Stata Corp, 2014a, 2014b).

Hoxby et al. (2008) suggests that a common view among researchers that the using non-parametric methods, when feasible, would produce evidence with the highest credibility. As mentioned above, exact matching employed in this study is a non-parametric approach, which inherently reflect no model specification assumptions and hence is robust to model misspecification risks. Furthermore, with categorical observable variables and large number of observations, the degree of feasibility of matching would be relatively much higher. As all the covariates used in this study are observable and the number of observations reaches over three million, implementation of matching estimator stands as a relevant approach at the outset. However, exact matching method requires strict obeyance to overlap assumption in order to identify the average treatment effect. This means that number of confounding covariates can be used are restricted by the degree of overlap of the data. Because of this limitation, consecutive implementation of exact matching and the other two methods is considered.

Hence, all three estimation methodologies estimate the same thing albeit under different strengths and weaknesses in terms of our identification assumptions and perils of insufficient model specification. So, if these different methodologies are to produce similar results, we can argue about the robustness of our results in a more confident manner.

Findings with Regression Adjustment

We start with the OLS regression model with assuming homogeneous treatment effects, which excludes potential interactions between treatment and other covariates. In that case average treatment effect would be equal to the average treatment effect on the treated since we assume homogenous, in other words same effect on each of the students. We can observe from Table-6 the changes in the coefficient of school type as we add more covariates to the regression equation. We start with adding just the covariate "year"; it only reduced the unadjusted difference between the two groups merely by one point. Then we add one-by-one the main potential confounders we identified in previous sections.

As expected, the group of covariates identified as the principal potential confounders showcased their potential and led to substantial revisions in the size of the coefficient.

Education levels of the father and the mother each lead to major reductions on the size of the coefficient of school type. Student's own room at home leads to a reduction but it is about half the size of the former two covariates. Moreover, in the instance we control for father's education and mother's education in together, the size of the coefficient falls to 52.69 points and we can say it stabilizes for the most part after that. Even the addition of student's own room at home, the third major potential confounder, affects it only slightly. This observation is in accordance with the findings of Phillips et al (1998), which suggests that the education level of the parents is the best single estimator of student academic achievement.

On the other hand, using city's development index instead of city's development priority and city's geographical region, as suggested in the previous sections, seems to not affect the estimate of the treatment effect. But it produces a lower root mean squared error, as seen from the comparison between Model 8 and Model 9, which makes it more desirable alternative. Another suggested control variable mentioned in the previous sections is the interaction term between education level of the father and the occupation type of the father. Addition of such a variable does not affect neither the estimate of the treatment effect nor the level of root mean squared error. So, after all fine-tuning, and assuming the model specification is correct, we end up with a mean homogeneous treatment effect of around 52 points with a narrow 95% confidence interval covering roughly half points less and half points more.

Table 6. Findings of OLS Models under the Assumption of Homogeneous Treatment Effects

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
School Type	135.4***	71.2***	69.4***	103.6***	52.7***	49.5***	50.5***	51.6***	50.4***	51.5***	52.2***	52.1***
Year	4.4***	4.1***	4.0***	3.8***	3.9***	3.5***	3.5***	3.7***	3.72***	3.7***	3.6***	3.6***
Father's Education		55.1***			41.8***	36.4***	35.9***	30.9***	31.3***	37.5***	30.7***	37.8***
Mother's Education			57.9***		30.6***	24.9***	23.5***	23.1***	23.6***	23.1***	23.5***	23.6***
Student's Own Room				59.7***		30.9***	27.0***	25.6***	27.3***	25.4***	25.5***	25.2***
City's Development Index							30.0***	30.9***		30.6***	31.3***	31***
Father's Occupation								12.0**	12.4***	18.7***	11.7***	19***
Mother's Occupation								0.07	-0.04	0.03***	0.5***	0.8***
Resident Type of Family								7.6***	7.1***	7.6***	7.2***	7.2***
City's Development Priority									1.55***			
City's Geographical Region									1.36***			
Father Interaction Term										2.9***		-3.2***
Gender of Student											30.6***	30.6***
Father's Life Status											15.2***	15.5***
Mother's Life Status											2.6**	2.7**
Parent's Marital Status											-18.9***	-19.0***
Root Mean Squared Error	96	87	89	90.5	85.5	84	83.5	83	83.5	83	81.5	81.5

Legend * p<0.05; ** p<0.01; *** p<0.001

Next, we once again implement OLS, but this time with interactions between the treatment variable and the other covariates. By doing this we address the case that difference in the treatment effect between the two groups may differ for students with different characteristics. ATE and ATET would be different in this case, and what we find from a margin analysis of school type coefficient would be ATE. Regression of BAS score over the set of covariates and the interaction terms of these covariates with the *school type* is conducted and then the average response is calculated to obtain an estimate for the mean heterogeneous treatment effect. So, after all of the fine-tuning, and assuming the model specification is correct, we end up with a mean heterogeneous treatment effect of around 88 points with a tiny 95% confidence interval covering roughly one points less and one point more. The case that the estimate under the heterogeneous effects is different than the estimate under the homogeneous effects provides evidence for the existence of heterogeneous treatment effects.

On the other hand, as in the version with homogeneous effect assumption, root mean squared error has improved until Model-11 and final inclusion of father interaction term (between his education and his occupation) does not lead to any change either in the estimate or in the root mean squared error. However, in Model-12 only the father interaction term can be added to model. When an interaction term between the school type and the father interaction term (i.e. triple interaction), the model could not be identified.

Table 7. Findings of OLS Models under the Assumption of Heterogeneous Treatment Effects

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
School Type	136.83	96.8	100.17	121.95	89.47	87.87	87.58	87.39	86.39	87.36	88.32	88.29
Root Mean Squared Error	96.5	87	89	90.5	85	84	83	83	83.5	83	81	81

Third and final approach in this section implements the use of Regression Adjustment Estimator based on Cattaneo (2010) and Cattaneo et al. (2013). As described in methods section, this estimator is an exactly identified GMM estimator that involve two steps. Table-8 presents the estimates with this indicator:

Table 8. Findings with Regression Adjustment Estimator (12 Different Models)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Average Treatment Effect (ATE)												
On all of the students	136.69	97.27	100.20	121.78	89.52	87.70	87.39	87.52	88.11	86.76	88.36	87.61
Potential Outcome Means												
If All of the Students Were Studied at Public	287.90	295.80	296.27	291.48	297.72	298.06	298.02	298.08	298.13	298.07	298.06	298.06
If All of the Students Were Studied at Private	424.59	393.07	396.47	413.26	387.24	385.76	385.41	385.60	386.24	384.83	386.42	385.67
Averga Treatment Effect on the Treated (ATET)												
On the students currently enrolled at private	135.38	69.48	65.88	103.28	49.29	46.98	48.12	49.19	48.01	49.16	49.72	49.69
Potential Outcome Mean												
If currently enrolled at private were to study at public	288.83	355.70	359.26	321.03	376.21	378.37	377.22	376.19	377.38	376.23	375.69	375.73

As expected, estimates for ATE and ATET are close to the ones achieved by the use of OLS-based estimators. Advantage of Regression Adjustment Estimator is that it produces these estimates together with potential outcome means. This shows that OLS is a valid estimator for causal inference if the required assumptions are met. However, as observed from Table-8, this time inclusion of father interaction term has a slight effect on the ATE in Model-12. OLS under heterogeneous treatment effects assumption could not identify this. So, for this study, Regression Adjustment Estimator has turned out to be a less restrictive method compared to OLS under the heterogeneous effects assumption.

Table 9. Results with Regression Adjustment Estimator with Model-12

Model-12		**Coefficient**	**Robust St. Error**	**z**	**[95% Confidence Interval]**	
Average Treatment Effect (ATE)						
	On all of the students (points)	87.61	0.44	168.67	[86.78	88.48]
	On all of the students (percentage)	29.39	0.00	197.73	[29.10	29.69]
Potential Outcome Means	If all of the students were studied at public	298.06	0.18	5298.07	[297.95	298.17]
	If all of the students were studied at private	385.68	0.44	879.70	[384.82	384.54]

Table 9. Continued

Model-12		**Coefficient**	**Robust St. Error**	**z**	**[95% Confidence Interval]**	
Average Treatment Effect on the Treated (ATET)						
Potential Outcome Mean	On the students currently enrolled at private	49.68	0.06	242.79	[49.28	50.08]
	If currently enrolled at private were to study at public	375.73	0.18	2113.95	[375.38	376.10]

Now, it's time to interpret our estimates. Assuming that the model specification is correct, and the strong ignorability of treatment assignment is valid, the interpretation of Average Treatment Effect (ATE) to the size of 87.6 points (29.4%) is such that the average BAS score if all of the students had studied at private schools would be 87.6 points more (29.4%) than the average BAS score if none of them had studied at private schools and hence all of them had studied at public schools. We can also see ATE as the average effect, at the population level, of moving an entire population from control to treated (Austin & Stuart, 2015).

The Potential Outcome for public school is interpreted as if none of the students had studied at private school (so all of them had studied at public schools), the expected average BAS score would be 298.06. Similarly, The Potential Outcome for private is interpreted as if all of the students had studied at private schools then the average BAS score would be 385.7 points.

The interpretation of Average Treatment Effect on the Treated (ATET) to the size of 49.7 points is such that the average BAS score is 49.7 points more when all the students studying at private schools do so than the average of 375.7 points that would have occurred if none of these students had studied at a private school.

Findings with Inverse Probability Weighting

First step of inverse probability weighting naturally involves the estimation of propensity scores. Correct specification of the modelling of treatment assignment mechanism is important here, for similar reasons we discussed for regression adjustment. Table-10 presents the results from alternative specifications that implement Probit regression. In the first model the major confounders and gender covariate are used. The reason for adding gender to them is due to Brookhart et al. (2006), who suggest that variables uncorrelated with treatment assignment but correlated with outcome shall always be included in the propensity score model for more precision.

Table 10. Alternative Specifications for Propensity Score Model (Probit Regressions)

Variable	**Model-1**	**Model-2**	**Model-3**	**Model-4**
Student's Own Room	0.57***	0.59***	0.57***	0.58***
Father's Education	0.41***	0.48***	0.48***	0.48***
Mother's Education	0.55***	0.51***	0.51***	0.51***
Gender of Student	-0.08***	-0.08***	-0.08***	-0.08***
Father's Occupation		-0.17***	-0.17***	-0.18***
Mother's Occupation		0.07***	0.06***	0.07***
City's Development Index		-0.05***	-0.04***	-0.04***
Resident Type of Family			0.16***	0.16***
Parent's Marital Status				-0.15***
Father's Life Status				0.06***
Mother's Life Status				-0.02
Constraint	-3.77***	-3.46***	-3.74***	-3.73***
Log Likelihood	-380268	-371084	-368701	-368466
Pseudo_R2	0.30	0.31	0.31	0.31

Figure-2 shows the distributions of estimated propensity scores for treated and untreated groups. They look comparable.

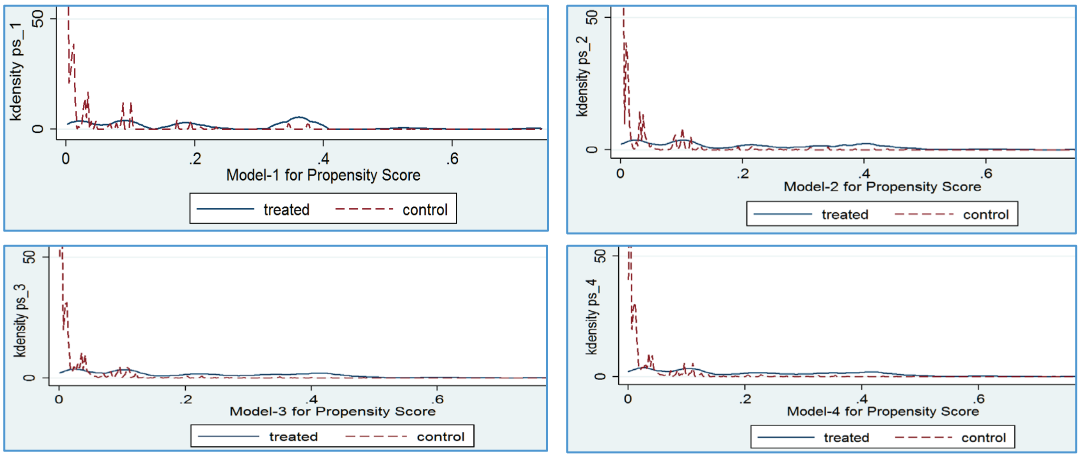

Figure 2. Propensity Score Distributions of Treatment and Control Groups

In Table 11, the results from IPW estimation are presented. Estimates are quite close. They are also in line with the estimates of regression based estimators we implemented in the previous section. As discussed before, IPW estimators are sensitive with respect to overlap assumption. They start to produce erratic estimates as the overlap assumption gets close to being violated. If that happens, certain subsets of the inverse-probability weights inflate and the large-sample distribution no longer qualifies as a sufficient approximation to the finite-sample distribution of IPW estimators. This erratic behavior persists even in the case of correct specification of the functional form for the treatment model is ensured. The last two parts of Table-11 addresses this important aspect. The lower parts of the distribution of the estimated probability of not getting treatment seems most vulnerable, since inverse of these probabilities would produce the weights and we do not desire very large weights. Fortunately, overlap assumption seems to be satisfactory with zero violations at e^{-5} and e^{-4} tolerance levels, which can be seen as threshold levels, for all models, and at e^{-3} level for the first model. First model also possess better distributional properties regarding the estimated probability of not getting treatment. Hence, as first model reflects the best properties in terms of fitness to overlap assumption, we can consider it as our preferred model.

Table 11. Inverse Probability Weighting Estimation Results

		Model -1				Model-2				Model-3				Model-4			
		Coef.	Robust Std. Error	[95% Confidence	Interval]	Coef.	Robust Std. Error	[95% Confidence	Interval]	Coef.	Robust Std. Error	[95% Confidence	Interval]	Coef.	Robust Std. Error	[95% Confidence	Interval]
Average Treatment Effect (ATE)																	
Potential Outcome Means	Private vs Public	87.22	0.65	[85.95	88.50]	87.70	0.69	[86.35	89.04]	87.29	0.72	[85.88	88.70]	87.04	0.73	[85.62	88.46]
	Public Schools	297.87	0.56	[297.77	297.98]	297.94	0.06	[297.83	298.05]	297.97	0.06	[297.86	298.08]	297.99	0.06	[297.88	298.10]
	Private Schools	385.10	0.65	[383.83	386.37]	385.63	0.68	[384.29	386.97]	385.26	0.72	[383.86	386.66]	385.03	0.72	[383.61	386.44]
Average Treatment Effect on the Treated (ATET)																	
Potential Outcome Mean	Private vs Public Counterfactual of Treated	51.29	0.21	[50.87	51.71]	52.60	0.22	[52.17	53.03]	51.80	0.22	[51.37	52.54]	51.34	0.22	[50.90	51.77]
	Public Counterfactual of Treated	374.08	0.18	[373.72	374.44]	372.90	0.19	[372.52	373.28]	373.61	0.20	[373.23	373.99]	374.08	0.20	[373.69	374.46]
	Tolerance Level for Checking Overlap	**# of Observations Violating Overlap Assumption**				**# of Observations Violating Overlap Assumption**				**# of Observations Violating Overlap Assumption**				**# of Observations Violating Overlap Assumption**			
Overlap Assumption Checks	**1e-5**	0				0				0				0			
	1e-4	0				0				0				0			
	1e-3	0				7,151				6,710				21,602			
	2e-3	584,007				335,682				355,714				354,760			
	5e-3	1,218,698				1,226,535				1,219,657				1,213,663			
	1e-2	1,526,586				1,633,449				1,534,322				1,542,450			
	1e-1	2,667,161				2,636,142				2,646,294				2,655,202			
		Estimated Probability of Getting Treatment		**Estimated Probability of Not Getting Treatment**		**Estimated Probability of Getting Treatment**		**Estimated Probability of Not Getting Treatment**		**Estimated Probability of Getting Treatment**		**Estimated Probability of Not Getting Treatment**		**Estimated Probability of Getting Treatment**		**Estimated Probability of Not Getting Treatment**	
Distributions of Estimated Probabilties of Getting and Not Getting the Treatment	**Yüzde**	**Percentiles**	**Smallest**	**Percentiles**	**Smallest**	**Percentiles**	**Smallest**	**Percentiles**	**Smallest**	**Percentiles**	**Smallest**	**Percentiles**	**Smallest**	**Percentiles**	**Smallest**	**Percentiles**	**Smallest**
	1%	0.26083	0.26083	0.00195	0.00195	0.21751	0.13959	0.00171	0.00055	0.23123	0.13171	0.00120	0.00036	0.22636	0.12686	0.00125	0.00020
	5%	0.46295	0.26083	0.00195	0.00195	0.41329	0.13959	0.00171	0.00055	0.40618	0.13171	0.00139	0.00036	0.40649	0.13068	0.00129	0.00020
	10%	0.62456	0.26083	0.00195	0.00195	0.53088	0.16661	0.00171	0.00055	0.53730	0.13400	0.00156	0.00036	0.54150	0.13068	0.00161	0.00020
	25%	0.65426	0.26083	0.00250	0.00195	0.61448	0.16661	0.00220	0.00055	0.62585	0.13400	0.00260	0.00036	0.62149	0.13068	0.00256	0.00020
	75%	0.91231	0.99805	0.03224	0.73917	0.91148	0.99933	0.03178	0.82850	0.91804	0.99954	0.03431	0.86600	0.91764	0.99957	0.03402	0.86932
	90%	0.97309	0.99805	0.10102	0.73917	0.98158	0.99945	0.10199	0.82850	0.98002	0.99957	0.09685	0.86600	0.98101	0.99957	0.09658	0.86932
	95%	0.98965	0.99805	0.17242	0.73917	0.99041	0.99945	0.14531	0.83339	0.98927	0.99957	0.15533	0.86600	0.98908	0.99963	0.15456	0.86932
	99%	0.99750	0.99805	0.37544	0.73917	0.99780	0.99945	0.38552	0.83339	0.99767	0.99964	0.38035	0.86600	0.99766	0.99972	0.37851	0.86932

We have implemented Probit regression to estimate the propensity scores, and as model specification is important, in this case we check for alternative estimation methods using our preferred configuration mentioned above. As seen in Table-12, first robustness check is made with implementation of Heteroskedastic Probit model. Results are in line with our preferred model. Second, we used Logit model and observe a slight increase in the estimate.

Table 12. Robustness Checks

Robustness Check with Heteroskedastic Probit Model Estimation		**Model - 1**			
		Coef.	**Robust Std. Error**	**[95% Confidence**	**Interval]**
Average Treatment Effect (ATE)					
	Private vs Public	87.86	0.65	[86.59	89.13]
Potential Outcome Means	Public Schools	297.97	0.06	[297.86	298.28]
	Private Schools	385.83	0.65	[384.56	387.10]
Average Treaatment Effect on the Treated (ATET)					
Potential Outcome Mean	Private vs Public Counterfactual of Treated	50.15	0.22	[49.72	50.57]
	Public Counterfactual of Treated	375.22	0.19	[374.85	375.59]
Robustness Check with Logit Model Estimation		**Model – 1**			
		Coef.	**Robust Std. Error**	**[95% Confidence**	**Interval]**
Average Treatment Effect (ATE)					
	Private vs Public	90.34	0.53	[89.31	91.37]
Potential Outcome Means	Public Schools	298.07	0.06	[297.96	298.18]
	Private Schools	388.41	0.52	[387.38	389.44]
Average Treaatment Effect on the Treated (ATET)					
Potential Outcome Mean	Private vs Public Counterfactual of Treated	49.17	0.23	[48.73	49.61]
	Public Counterfactual of Treated	376.20	0.20	[375.80	376.60]

In order to assess which model specification is right, we can take the advantage of doubly robust property of *augmented inverse probability weighting* method (Robins & Rotnitzky, 1995). This doubly-robust estimator can tolerate for wrong specification of one the models, RA or IPW, as long as one of them is correctly specified. However, as this method is only suitable to produce estimates of ATE but not ATET, inverse probability weighted regression adjustment, which also has doubly-robust property, is employed for the estimation of ATET (Wooldridge, 2010). As IPW estimator modelled with Probit regression is quite close to the estimates of regression approach, we would use logit for the IPW part of doubly-robust estimator. If IPWR results turn out to be similar with regression adjustment estimator, then we can argue that IPW under Probit model is correct. Otherwise, we shall regard model specification with regression problematic as well as the Probit modelling approach. Both models could be wrong as well, then IPWR estimator is not useful. This is one of the reasons for using Exact Matching Estimator that we will deal with in the following section; we will also compare the results found in this section with the findings of that section. Table-13 presents the findings for doubly-robust estimator.

Table 13. Findings for Doubly Robust Estimation

REGRESSION ADJUSTMENT	Covariates Employed: Regression Adjustment with Model-12 Covariates	Coef.	Robust Std. Error	[95% Confidence Interval]	
Average Treatment Effect					
Potential Outcome Means	On all of the students	87.61	0.44	[86.74	88.48]
	If all students were to study at public	298.06	0.06	[297.95	298.17]
	If all students were to study at private	385.68	0.44	[384.82	386.54]
Average Treatment Effect on the Treated					
Potential Outcome Mean	On students currently enrolled at private	49.68	0.20	[49.28	50.08]
	If students currently studyig at private were to study at public	375.73	0.18	[375.38	376.10]
DOUBLY-ROBUST ESTIMATOR (with LOGIT)	**Covariates Employed: Regression Adjustment with Model-12 Covariates and Inverse Probabability Weigthing with Model-A**	**Coef.**	**Robust Std. Error**	**[95% Confidence Interval]**	
Average Treatment Effect					
Potential Outcome Means	On all of the students	87.52	0.55	[86.45	88.57]
	If all students were to study at public	297.95	0.06	[297.84	298.06]
	If all students were to study at private	385.46	0.54	[384.40	386.53]
Average Treatment Effect on the Treated					
Potential Outcome Mean	On students currently enrolled at private	51.33	0.23	[50.88	51.79]
	If students currently studyig at private were to study at public	374.10	0.21	[373.67	374.48]
DOUBLY-ROBUST ESTIMATOR (with PROBIT)	**Covariates Employed: Regression Adjustment with Model-12 Covariates and Inverse Probabability Weigthing with Model-A**	**Coef.**	**Robust Std. Error**	**[95% Confidence Interval]**	
Average Treatment Effect					
Potential Outcome Means	On all of the students	87.71	0.66	[86.41	89.01]
	If all students were to study at public	297.99	0.06	[297.88	298.10]
	If all students were to study at private	385.70	0.66	[384.40	387.00]
Average Treatment Effect on the Treated					
Potential Outcome Mean	On students currently enrolled at private	50.70	0.22	[50.26	51.13]
	If students currently studyig at private were to study at public	374.72	0.19	[374.34	375.10]

Findings with Matching

Matching is a non-parametric approach, which means vulnerabilities related to model specification do not apply to this estimator. Exact matching technique is applied in this study involves computing the difference between the outcomes related to the treatment group and the control group within each strata formed by the different combinations of covariates related to students. The main restriction of exact matching estimator on the other hand is that the set of covariates employed are restricted by the overlap assumption.

Table 14 presents the results with the largest set of covariates under this restriction, which involves four covariates. Fortunately, this at least enables us to account for all four major potential confounders: Father's education, mother's education, student's own room at home, and development index of the city. It is readily observed that treated group has higher average scores across all strata.

Table 14. Exact Matching Results for Each Matched Strata

Exact Matching Strata	Public Schools						Private Schools					
Student's Own Room - Father's Education - Mother's Education- City's Development Index	**Frequency**	**Coefficent**	**Robust Std. Error**	**t**	**[95% Confidence Interval]**		**Frequency**	**Coefficent**	**Robust Std. Error**	**t**	**[95% Confidence Interval]**	
None-Up to Primary-Up to Primary-High Priority	297,816	230.43	0.17	1380.44	[230.11	230.76]	470	352.54	3.98	88.62	[344.74	360.33]
None-Up to Primary-Up to Primary-Low Priority	918,311	262.81	0.09	2929.18	[262.63	262.98]	2,231	370.21	1.69	219.19	[366.90	373.52]
None-Up to Primary- Secondary/Tertiary-High Priority	3,118	264.71	1.60	165.02	[261.56	267.85]	36	346.30	11.04	31.35	[324.66	367.95]
None-Up to Primary- Secondary/Tertiary-Low Priority	48,119	296.33	0.38	770.44	[295.58	297.09]	510	387.94	3.31	117.06	[381.45	394.44]
None-Up to Primary-Bs/Ms/PhD-High Priority	135	271.19	8.68	31.25	[254.18	288.20]	3	410.80	57.50	7.14	[298.10	523.50]
None Up to Primary-Bs/Ms/PhD-Low Priority	1,796	308.22	2.13	145.01	[304.05	312.39]	62	405.63	8.92	45.46	[388.14	423.12]
None-Secondary/Tertiary-Up to Primary/High Priority	45,340	273.00	0.41	660.79	[272.19	273.81]	317	367.48	4.51	81.49	[358.64	376.32]
None-Secondary/Tertiary-Up to Primary-Low Priority	235,590	300.93	0.17	1725.62	[300.59	301.28]	1,852	388.16	1.67	231.74	[384.88	391.44]
None-Secondary/Tertiary-Secondary/Tertiary-High Priority	6,707	292.11	1.07	273.39	[290.01	294.20]	139	384.91	5.81	66.26	[373.52	396.29]
None-Secondary/Tertiary-Secondary/Tertiary-Low Priority	85,997	320.02	0.29	1104.50	[319.45	320.58]	1,932	399.89	1.56	256.10	[396.83	402.95]
None-Secondary/Tertiary-Bs/Ms/Phd-High Priority	143	340.25	7.95	42.79	[324.66	355.83]	13	356.40	22.88	15.58	[311.56	401.24]
None-Secondary/Tertiary-Bs/Ms/Phd-Low Priority	3,666	362.79	1.33	271.93	[360.17	365.40]	343	418.51	3.33	125.72	[411.98	425.03]
None-Bs/Ms/PhD-Up to Primary-High Priority	4,953	319.11	1.26	252.30	[316.63	321.59]	144	404.83	6.62	61.18	[391.86	417.80]
None-Bs/Ms/PhD-Up to Primary-Low Priority	22,867	351.04	0.56	630.90	[349.95	352.13]	777	417.68	2.44	170.84	[412.89	422.47]
None-Bs/Ms/PhD-Secondary/Tertiary-High Priority	1,218	357.36	2.42	147.72	[352.62	362.10]	111	427.91	5.61	76.26	[416.91	438.91]
None-Bs/Ms/PhD-Secondary/Tertiary-Low Priority	16,255	377.74	0.61	619.83	[376.55	378.94]	1,485	432.48	1.43	303.09	[429.68	435.28]
None-Bs/Ms/PhD-Bs/Ms/PhD-High Priority	214	387.16	5.84	66.29	[375.72	398.61]	75	448.11	5.70	78.65	[436.94	459.28]
None-Bs/Ms/PhD-Bs/Ms/PhD-Low Priority	6,381	409.68	0.90	453.40	[407.91	411.45]	2,216	451.10	1.00	450.11	[449.13	453.06]
Exists-Up to Primary-Up to Primary-High Priority	29,823	263.55	0.52	508.17	[262.54	264.57]	483	360.98	3.42	105.48	[354.27	367.69]
Exists-Up to Primary-Up to Primary-Low Priority	412,451	292.65	0.13	2264.65	[292.39	292.90]	6,334	374.09	0.92	405.74	[372.29	375.90]
Exists-Up to Primary-Secondary/Tertiary-High Priority	1,375	304.16	2.34	129.74	[299.57	308.76]	126	376.42	6.47	58.22	[363.75	389.10]
Exists-Up to Primary-Secondary/Tertiary-Low Priority	67,175	319.79	0.32	1010.03	[319.17	320.41]	2,898	388.34	1.29	300.08	[385.80	390.87]
Exists-Up to Primary-Bs/Ms/PhD-High Priority	80	318.89	9.85	32.36	[299.58	338.20]	8	363.42	26.59	13.67	[311.30	415.54]
Exists-Up to Primary-Bs/Ms/PhD-Low Priority	3,794	344.07	1.38	248.67	[341.36	346.79]	542	414.45	2.82	146.99	[408.92	419.98]
Exists-Secondary/Tertiary-Up to Primary/High Priority	18,523	302.65	0.63	479.69	[301.42	303.89]	771	377.08	2.63	143.60	[371.93	382.22]
Exists-Secondary/Tertiary-Up to Primary-Low Priority	241,098	322.78	0.17	1934.46	[322.45	323.10]	7,456	389.08	0.82	475.57	[387.47	390.68]
Exists-Secondary/Tertiary- Secondary/Tertiary-High Priority	8,057	329.03	0.94	349.66	[327.19	330.87]	928	393.36	2.25	174.64	[388.95	397.78]
Exists-Secondary/Tertiary- Secondary/Tertiary-Low Priority	223,785	344.00	0.17	2022.84	[343.67	344.34]	20,141	403.29	0.46	867.97	[402.38	404.20]
Exists-Secondary/Tertiary-Bs/Ms/Phd-High Priority	571	376.17	3.15	119.41	[369.99	382.34]	182	421.06	4.85	86.84	[411.56	430.57]
Exists-Secondary/Tertiary-Bs/Ms/Phd-Low Priority	24,735	383.47	0.48	805.22	[382.54	384.40]	6,657	426.28	0.72	595.08	[424.88	427.69]
Exists-Bs/Ms/PhD-Up to Primary-High Priority	5,361	350.88	1.16	303.17	[348.61	353.15]	471	410.13	3.05	134.31	[404.15	416.12]
Exists-Bs/Ms/PhD-Up to Primary-Low Priority	46,642	369.06	0.36	1016.63	[368.35	369.77]	3,655	421.01	1.03	407.51	[418.98	423.03]
Exists-Bs/Ms/PhD-Secondary/Tertiary-High Priority	4,242	378.01	1.24	305.78	[375.58	380.43]	1,064	427.81	1.82	234.72	[424.24	431.38]
Exists-Bs/Ms/PhD-Secondary/Tertiary-Low Priority	81,494	389.82	0.26	1524.59	[389.32	390.32]	16,977	431.58	0.43	993.35	[430.73	432.44]
Exists-Bs/Ms/PhD-Bs/Ms/PhD-High Priority	1,690	415.46	1.78	233.12	[411.97	418.95]	1,502	456.55	1.18	387.32	[454.24	458.86]
Exists-Bs/Ms/PhD-Bs/Ms/PhD-Low Priority	66,694	422.35	0.25	1690.78	[421.86	422.84]	49,502	453.31	0.21	2152.97	[452.90	453.72]
Total	**2,936,216**						**132,413**					

Table-15 presents the estimate of ATE under the use of exact matching estimator, which corresponds to 87.04 points.

Table 15. Results with Exact Matching Estimator

Average Treatment Effecet	Coefficient	Std. Error	[95% Confidence Interval]	
On all of the students	87.04	0.72	[85.62	88.46]

Discussion

In the context of the findings, education levels of father and mother, existence of the own room of the student at home, and the status of the city indicating if it is in the group of the least developed cities or not are found to be the strong confounders in this study. As expected, strong confounders accounted for the major part of the bias. As other methods have produced almost the same estimates, we can conclude that, functional form is correctly set at least for the set of the four strong confounders.

Table 16. Average Treatment Effect Estimates with Using Only Four Strong Confounders

Method	Coefficient	Std. Error	[95% Confidence Interval]	
Exact Matching	87.04	0.72	[85.62	88.46]
OLS under heterogeneous effect assumption	87.16	0.49	[86.21	88.11]
Regression Adjustment Estimator	87.12	0.43	[86.28	87.96]
Reverse Probability Weighting (with Probit)	87.22	0.65	[85.95	88.50]

Getting relieved from the major part of our concerns related to functional form misspecification, the estimates of average treatment effect, average treatment effect on the treated, and potential outcome means under the strong ignorability of treatment assignment assumption are presented in Table-17, which involves findings from regression adjustment estimates under Model-12, from inverse probability weighting estimates with Model-A and Probit, and from the doubly-robust estimator.

Table 17. Summary of Estimates of Causal Effects from Different Methods

REGRESSION ADJUSTMENT ESTIMATOR		Coeff.	Robust Std. Error	[95% Confidence Interval]	
Average Treatment Effect					
	On all of the students	87.61	0.44	[86.78	88.48]
Potential Outcome Means	If all students were to study at public	298.06	0.06	[297.95	298.17]
	If all students were to study at private	385.68	0.44	[384.82	384.54]
Average Treatment Effect on the Treated					
Potential Outcome Mean	On students currently enrolled at private	49.68	0.06	[49.28	50.08]
	If students currently studyig at private were to study at public	375.73	0.18	[375.38	376.10]
INVERSE PROBABILITY WEIGHTING		**Coeff.**	**Robust Std. Error**	**[95% Confidence Interval]**	
Average Treatment Effect					
	On all of the students	87.22	0.65	[85.95	88.50]
Potential Outcome Means	If all students were to study at public	297.87	0.06	[297.77	297.98]
	If all students were to study at private	385.10	0.65	[383.83	386.37]
Average Treatment Effect on the Treated					
Potential Outcome Mean	On students currently enrolled at private	51.29	0.21	[50.87	51.71]
	If students currently studyig at private were to study at public	374.08	0.18	[373.72	374.44]

Table 17. Continued

DOUBLY-ROBUST ESTIMATOR		Coeff.	Robust Std. Error	[95% Confidence Interval]	
Average Treatment Effect					
Potential Outcome Means	On all of the students	87.71	0.66	[86.41	89.01]
	If all students were to study at public	297.99	0.06	[297.88	298.10]
	If all students were to study at private	385.70	0.66	[384.40	387.00]
Average Treatment Effect on the Treated					
Potential Outcome Mean	On students currently enrolled at private	50.70	0.22	[50.26	51.13]
	If students currently studyig at private were to study at public	374.72	0.19	[374.34	375.10]

The findings in Table-17 are quite close, which sets ground for the robustness of the results. It is noticeable that estimates remain the same even if fourteen covariates are included in the models compared to the findings with only four strong confounders. This is in line with the arguments given above regarding strong confounders. Estimates with the doubly-robust estimator are interpreted below:

Under the assumption of strong ignorable treatment assignment, findings indicate that studying at a private school leads to 87.7 points increase in BAS score on average. If all of the students in Turkey had studied at public schools, the expected average BAS score would be 298. Similarly, if all of the students in Turkey had studied at private schools then the average BAS score would be 385.7. This corresponds to a 29.4 per cent improvement for studying at a private school over studying at a public school on average. Moreover, the contribution of studying at a private school to the average BAS score to the students currently enrolled in private schools corresponds to 50.7 points over the 374.7 points of average BAS score that would have realized if those specific group of students were to be enrolled at public schools. What these results tell us is that studying at a private school increases the achievement across all students by a considerable margin, and its contribution would be even higher for the group which does not have access to it.

As emphasized before, unbiasedness of above estimates depend on the validity of the strongly ignorable treatment assignment assumption. An important aspect of this assumption is that the there are no unobserved confounders; at least no strong unobserved confounders. As this assumption is not testable, arguments for its validity is to be motivated by previous literature, field expertise, and intuition. An important objective of this study is to set forward a rigorous approach for this task. In this context confounding potential of two unobserved factors, first of which is the unobservable intrinsic ability and/or motivation of the student, second is the distance of between the school and the home of the student, which is unobserved due to lack of data, are elaborated and reasons are given why they are not expected to be as such. Double-correlation criteria required for confounding plays the key role in those elaborations. For example, intrinsic ability and/or motivation, which is often cited in the literature, is expected to be correlated with educational achievement, however in order that this factor can be considered as a confounder, it also needs to be correlated with the treatment assignment; in other words, parents of students possessing higher ability and/or motivation should be more inclined to send their children to private school. However, just the opposite of this could also be true as parents could be more inclined to send their children possessing lower ability and/or motivation to private school in order to eliminate this disadvantage. If these two inclinations balance out each other, then there would be no confounding. As seen this example, double-correlation criteria sets a potent framework on how to elaborate on the confounding potential of unobserved factors and saves us from acting on the superfluous and vague arguments about confounding. This reasoning approach is recommended for similar studies on causal impacts.

Conclusion and Suggestions

This study aimed to estimate the causal impact of school type on the student achievement. Schools type involved two categories: public schools and private schools; whereas student achievement is defined in terms of an overall measure named BAS score (Basis for Admission score), which is a weighted score reflecting both the grades obtained from courses in each school and the points obtained at nation-wide centralized exams. Study utilized a dataset comprising 3,752,374 secondary school students, which covers all of the student population within 2014-2016 period. This comprehensive dataset is utilized for the first time.

At the first step, we have presented the literature on the effects of school type of test scores and similar student achievement indicators. This literature can be traced back to 1960's and its prominent aspect is the central role of methodology. On the other hand, a second line of literature, which focuses on the evaluation of causal effects of policies and of programs has progressed swiftly starting from 1980's (Imbens & Rubin, 2015; Imbens & Wooldridge, 2009) and promises an important methodological framework for evaluation of policies and programs in education science (Schlotter, Schwerdt, & Woessmann, 2010). The methodology of this study is designed by bringing together the mentioned two lines of research and is applied for the first time in this context in Turkey.

Methodology involved the application of regression adjustment, inverse probability weighting, and exact matching techniques in a complementary style. Each of these three different methods have different strengths and weaknesses; but as they rely on the same underlying identification assumptions, their converging estimates improved the robustness of estimations of our study. The details of the estimates are presented and discussed in detail within the discussion section.

Under the assumptions discussed within methodology and discussion sections, we have found that school type has significant impact on student achievement. This finding is in line with Berberoğlu et al. (2005), Arslan et al. (2006), Sulku and Abdioğlu (2015) Mohammadi et al. (2011) In this context, being a private school student instead of public school student leads to an 87 points increase (29,6%) on average in BAS score. On the other hand, findings of literature varies from no significant difference to positive difference between the two different school types similar to the findings of this study (Abdulkadiroglu et al., 2009; Angrist et al., 2011; Chingos & West, 2015; Frenette & Chan, 2015; Hoxby & Rockoff, 2004). However the size of the difference is considerably smaller in other countries compared to Turkey. This indicates that school type has a comparatively larger effect in Turkey. This finding is line with the similar findings of Berberoğlu et al. (2005), which utilized data of PISA studies and data from university entrance exam in Turkey and of Sulku and Abdioğlu (2015) who utilized TIMMS 2011 data.

Several conclusions can be suggested depending on the above findings. First, if we look at from the equal opportunities perspective (Tunç, 1969; Sarıer; 2010), enrollment to a private school is not an option for every student since this is closely related to the financial situation of the family. Only partial scholarships are provided by the government and hence families from lowest quantiles of income cannot cover the complimentary part of the tuiton. So, from the social inclusion perspective, findings of this study indicate the need for polices and instruments that will increase the performance of public schools. While it is beyond the scope this study to propose exact policies and actions, we can suggest following further studies inspired by the literature covered within this study:

It might be useful to conduct further analyses to understand which mechanisms are in action to trigger higher student achievement. Following factors are identified within the literature: More knowledgeable, communicable and attentive teachers, less crowded and more ergonomic classrooms, better curriculum design, better presentation of the course content, more learning resources including the more sophisticated and more effective use of learning technologies, less number of problems related to discipline, provision of more cultural capital inputs might facilitate the learning process of student as well as motivating them to do more homework, not to miss classes, to concentrate mode in the class, to feel satisfaction and joy from studying and learning. On the other hand, some other mechanisms could also play a role. For example, successful teachers employed in public schools might be transferred to private schools for several reasons. If that is the case, than issues such as wages and work conditions for teachers shall be addressed (Hoxby et al., 2008; Center on Education Policy, 2007; Önder, 2016, World Bank, 2011). "Mediation analysis" (Iacobucci, 2008) techniques may facilitate the identification of respective potential role of each of the suggested factors.

In addition to proposing further studies on improving the performance of public schools, we may also suggest some improvements on the scholarships provided the state. Scholarships for enrollment in private schools cover just a portion of the tuition, and the assignment of the scholarship does not depend on the student's academic performance. Scholarship decision depends on other factors such as financial status of the family, number of siblings, etc (MEB, 2017). As expressed before, partial scholarships are not an appropriate mechanism for the students from mostly disadvantaged families. We suggest the consideration of an alternative policy of making some of the scholarships conditional on the academic achievement to boost the attainment of bright students from mentioned disadvantaged groups.

The school type effects also need not to be restricted to the students themselves but well extend to their parents. More frequent and better-targeted inputs from private schools to the parents may increase the motivation of parents so that they become more attentive and helpful for their children's learning process. Additionally, it could also be the case that investing a sizable amount of financial resources to the private school might be a factor that motivate the parents to be more attentive and helpful so that they guarantee the maximum yield from their investment (Center on Education Policy, 2007; Dinçer, Alper, & Uysal Kolaşin (2009).

The overall mean effects of school type are summarized in Table-17 and stratified mean effects in terms of family and region are provided in Tablo-14. These estimates can be informative in terms of family decision regarding the school type. Mentioned decision can be affects in both ways. After comparing the estimated school effects and the relative costs of each school type, some of the parents might consider cost/benefit ratio sufficient, while some other parents might think the opposite. In all occasions, provision of such an information is deemed to be useful.

In order to isolate the effect of school type, other potential factors which are highlighted in the literature for their association with the student achievement were also analyzed. In this context strong association is found between student achievement and father's education, mother's education, existence of own room of the student at home, and the development level of the region family lives. This finding is in line with majority of the findings in the literature (Arı, 2007; Ataman & Epir 1972; Barr, 2015; Bourdieu et al., 2014; Ceylan & Berberoğlu, 2007; Dobbie & Fryer, 2011; Engin-Demir, 2009; Fındık & Kavak, 2013; Gürsakal, 2012; Güvendir, 2014; Lareau & Horvat; 1999; Lee & Burkham, 2002; Koğar, 2015; Özbay, 2015; Özdemir & Gelbal, 2014; White, 1982; Yağmurlu et al., 2009; Yayan & Berberoğlu, 2004; Yelgün & Karaman, 2015).

One of the most crucial issues for studies similar to this study to achieve more precise estimates under less restrictive assumptions is access to data. Especially, crucial responsibility is on the shoulders of related public organizations. We think that if the context, objectives, and data requirements of the studies are decided in collaboration of the public officials and the academic researchers, and if the data is provided by the public organizations, we will see much improved research output in the field of education sciences. For example, in the context of our study, if appropriate instrumental variables are found and if the data related to them are provided by the related public organizations, the assumptions regarding the unobservable factors can be revoked.

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