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Impacts of playing after school on academic performance: a propensity score matching approach

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ABSTRACT
We present a plausible causal analysis of the impact of playing after school on academic performance and investigate parental support as a potential channel. We exploit the data from the 2011 Trends in International Mathematics and Science Survey to evaluate the effects by using a propensity score matching approach. The results show that playing after school increases math and science scores of fourth grade students. We find that White students benefit from playing after school, but non-White students do not. Furthermore, we present evidence that parental support enhances the effects of playing after school.

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Academic performance; parental support; play after school; propensity score matching

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1. Introduction

After school activities usually involve, but are not limited to, playing on a sports team, studying in an art class, or participating in a Girl's Club/Girl's Scout or Boy's Club (hereinafter referred to as club). Participating in after school physical activities is important for children and adolescents. It is particularly important for the health of children aged 8–11 as part of their regular daily exercise due to their vulnerability at this stage of their lives (Silverstein et al. 2005; Hjorth, Chaput, Ritz, et al. 2014; Hjorth, Chaput, Damsgaard, et al. 2014).[1]

Participation in after school physical activities not only promotes a healthy and active lifestyle, but also fosters desired character traits of children (Dunn, Kinney, and Hofferth 2003; Strong et al. 2005). Evidence suggests there are positive effects of participating in after school activities on physical fitness, anxiety/depression symptoms, social communication skills and academic performance of students (Cooper et al. 1999; Cosden et al. 2004; Simpkins et al. 2005; Fauth, Roth, and Brooks-Gunn 2007). Current research has been conducted to examine the impacts of physical activities and sports participation on academic performance using different measures for academic performance in the literature. Yet there is no consistent evidence of the impacts on academic studies. For example, Esteban-Cornejo et al. (2014) find a weakly negative association between physical activities and academic performance; while Suchert, Hanewinkel, and Isensee (2016) show significant positive effects, and similar evidence is seen in Barron, Ewing, and Waddell (2000), Rees and Sabia (2010), Eide and Ronan (2001) as well.

Thus, there is no consensus of the magnitude of the effects of structured and organized after school physical activities (Cosden et al. 2004; Fauth, Roth, and Brooks-Gunn 2007; Trudeau and Shephard 2008). There have been intervention programs using small-scale survey data, but usually they are jeopardized by a lack of generality regarding the size of the estimated effects (Keeley and Fox 2009; Edwards, Mauch, and Winkelman 2011; Singh et al. 2012). Yet an in-depth understanding

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of the effects of after school activities on the academic performance of children is relevant for both practitioner and scholars.

In this study, we examine structured and organized after school physical activities, rather than unstructured activities which are more associated with 'latchkey children'. We pay special attention to structured and organized activities because the results of our study can provide policy guidance/ implications for school authorities, researchers and other stakeholders. Moreover, we focus on after school activities that involve physical activities (hereinafter referred to as 'playing after school'). Other after school activities that are more sedentary, such as studying in an art class, are not included in the analysis. We document the effects of playing after school (specifically consisting of playing on a sports team or belonging to a Girl's Club/Girl's Scout or Boy's Club) on academic performance among fourth grade students. The data used in this study are from a large-scale survey conducted in the United States.[2]

Our research addresses several issues that are unhandled in previous literature. First of all, intervention programs have limitations in their external validity due to a limited number of observations and heterogeneity in participant's socioeconomic status (SES). Thus, the conclusions might not be generalizable to a larger population. The data from the Trends in International Mathematics and Science Study (TIMSS) used in this study consists of representative observations of students, schools and teachers across the United States.

Secondly, we attempt to provide a causal link between playing after school and the academic performance of children. Normally ordinary least squares (OLS) estimations fail to address potential endogeneity issues resulting from self-selection bias and mutual influence. For example, students who participate in after school physical activities may be more active and intelligent, thus performing better in academic studies. Meanwhile, students who keep a good academic record may play after school a lot more due to a high level of motivation. Therefore, unless the endogeneity issues are properly accounted for, OLS estimations have limited causal inference. Recent studies employ an instrumental variable approach or a fixed effect model to address the endogeneity issue (Lipscomb 2007; Pfeifer and Cornelißen 2010; Rees and Sabia 2010). The purpose of this article is to identify the causal inference through a propensity score matching (PSM) approach (Rosenbaum and Rubin 1983). The PSM approach is built on Rubin's causal model (Rubin 1974). The predicted propensity score is the probability of students being in the treatment group of playing after school. This score summarizes the dissimilarity between students in the *treatment* group (i.e. who play after school) and the *control* group (i.e. who do not play after school) according to observed covariates that determine treatment participation. Conditional on the propensity score and identifying assumptions, playing after school is thought to be exogenous. Thus, academic performance is comparable for students with the same propensity score from the treatment and control groups.

Last but not least, the relationship between playing after school and academic performance might work through several channels. In addition to intrinsic characteristics of students, the extent of playing after school affecting academic performance also depends on extrinsic factors such as parental support (Fauth, Roth, and Brooks-Gunn 2007; Dunn, Kinney, and Hofferth 2003). Thus, we propose one plausible channel via parental support. To validate this channel, we conduct the analysis by separating the overall sample into two subgroups of students based on different levels of parental support, and then compare the results.

The results indicate that playing after school significantly increases math and science test scores. We also uncover heterogeneous effects of playing after school by racial/ethnic subgroups. More specifically, White students benefit from playing after school but non-White students do not. These findings are consistent with previous literature that studies diverse effects of sports participation on academic performance for racial/ethnic groups (Eide and Ronan 2001; Eitle and Eitle 2002; Johnston, Delva, and O'Malley 2007). Furthermore, we find high (low) levels of parental support enhances (reduces) the effects of playing after school. We believe that this effect is manifested through parents helping their children effectively manage their time after school.

The rest of the paper proceeds as follows. Section 2 outlines the empirical strategy. Section 3 describes the data. Section 4 conducts several diagnostic tests and presents the results. Section 5 presents a discussion of the results. Section 6 concludes.

2. Methodology

2.1. Identification strategy

A random assignment in the experimental setting ensures observations from the control and treatment group have similar characteristics. However, an ideal random experiment is usually not feasible because of high costs and ethical issues. The concept of PSM is to match treated participants to non-treated participants with similar characteristics (Rubin 1974; Rosenbaum and Rubin 1983; Dehejia and Wahba 1999). This underlying assumption is known as 'selection on observables' (Caliendo and Kopeinig 2008; Apel and Sweeten 2010). Although OLS estimation shares similarities in terms of 'selection on observables' as indicated in Apel and Sweeten (2010), PSM outperforms OLS for two reasons. First, PSM uses non-parametric matching with a common support, allowing a comparison between the treated participants and their resembling counterparts. Second, PSM provides causal inference while OLS does not. Moreover, instead of using high dimensional matching functions of observed covariates, the propensity score is a simplified unidimensional probability which is defined as 'the probability of participating in a program given observed individual characteristics' (Rosenbaum and Rubin 1983; Caliendo and Kopeinig 2008; Austin 2011).

The matching quality relies on the balance of the covariates. The balancing property indicates that matching variables of the treated group and the untreated group fall into the same distribution (Caliendo and Kopeinig 2008). Only when students in the *treated* group are *equivalent* to their counterfactuals in the *control* group (which means achieving balance), the comparison between them is feasible.

To account for the differences between treated and untreated students, we include a rich set of covariates associated with the treatment participation of students. Furthermore, we use student's engagement level in math and science as a proxy variable for the unobserved *motivation*. There are four sets of matching variables included in the analysis. Student characteristics include age, gender and race/ethnicity and the proxy variable for motivation. Household characteristics include the household facilities, which are highly correlated with family income and parent's education. School characteristics include the school types, school location, economic status composition of students in the school, discipline, and school schedule. Teacher characteristics include their gender and teaching experience. We also include variables of whether parents supervise their children's homework and students playing a musical instrument as matching variables to control for other after school activities. Table 1 displays all the matching variables mentioned above. We report the means and p-values to show the differences between students who play after school and those who do not play after school before and after matching. The t-tests indicate that students in the control group and the treatment group are significantly different in most characteristics only *before* matching. These differences disappear and are no longer statistically significant *after* matching. The last column of Table 1 shows the results of a logistic regression of treatment participation on these observed characteristics. Predictors of 'playing after school' include a set of variables, including student gender, race and household resources, characteristics of schools and the gender of teachers.

2.2. Assumptions

Two assumptions are required to validate the identification strategy (Caliendo and Kopeinig 2008; Rosenbaum and Rubin 1983).

Table 1. Covariates – summary statistics and the propensity score.

	Before matching			After matching			PSM logit
	Treated	Control	*P* value	Treated	Control	*P* value	Coeff
Student characteristics							
Student age	10.213	10.207	.507	10.213	10.218	.545	0.012
Student gender: female	0.473	0.569	.000	0.473	0.464	.323	−0.394***
Race: Whites = 1	0.572	0.408	.000	0.572	0.569	.729	0.217**
Race: Blacks = 1	0.105	0.111	.352	0.105	0.108	.616	0.098
Race: Hispanics = 1	0.217	0.333	.000	0.217	0.219	.732	−0.249**
Race: Asians = 1	0.034	0.077	.000	0.034	0.035	.817	−0.919***
Race: multiracial/other = 1	0.073	0.072	.846	0.073	0.070	.518	0.000
Engagement level (math)	10.176	10.082	.022	10.176	10.128	.162	0.031**
Engagement level (science)	10.319	10.251	.112	10.319	10.308	.770	0.000
Household characteristics							
Have computer at home	0.960	0.920	.000	0.960	0.957	.451	0.141
Have own room at home	0.775	0.648	.000	0.775	0.773	.827	0.400***
Have videogame at home	0.966	0.933	.000	0.966	0.963	.452	0.417***
Have internet at home	0.897	0.820	.000	0.897	0.893	.483	0.316***
Frequency of using computer: high	0.828	0.783	.000	0.828	0.835	.306	0.064
School characteristics							
Percent of students of economic disadvantage	0.359	0.520	.000	0.359	0.363	.581	−0.397***
Type of school: public = 1	0.982	0.990	.003	0.982	0.980	.420	−0.257
Students composition: more affluent	0.195	0.131	.000	0.195	0.196	.872	0.078
School location: low income area	0.322	0.436	.000	0.322	0.323	.864	−0.121
School location: medium income area	0.597	0.512	.000	0.597	0.597	.963	−0.139
School location: high income area	0.081	0.051	.000	0.081	0.080	.833	0.000
School emphasis on students' academic success	0.850	0.828	.005	0.850	0.849	.942	0.049
School discipline: high	0.614	0.572	.000	0.614	0.615	.883	−0.012
School help: parent deal with homework	0.627	0.645	.083	0.627	0.622	.539	−0.129*
School provide supervising material	0.419	0.416	.737	0.419	0.415	.620	0.048
Days in school per week	4.998	5.000	.162	4.998	4.998	.933	−0.243
Total hours for school daily	6.022	6.056	.034	6.022	6.022	.964	−0.046
Teacher characteristics							
Teacher gender: female	0.862	0.870	.310	0.862	0.862	.954	−0.153*
Experience: less than five years	0.141	0.169	.000	0.141	0.141	.931	−0.139
Experience: five to 20 years	0.617	0.599	.078	0.617	0.620	.795	0.011
Experience: more than 20 years	0.241	0.232	.321	0.241	0.239	.823	0.000
Parents check homework	0.881	0.841	.000	0.881	0.881	.913	0.297***
Play instrument	0.382	0.314	.000	0.382	0.385	.704	0.259***

*$p < .1$.
**$p < .05$.
***$p < .01$.

Assumption 1 Unconfoundedness $Y(1), Y(0) \perp\!\!\!\perp D|X$

$Y(1)$ and $Y(0)$ are outcomes for the treated and untreated, respectively. D stands for the treatment and X are observed covariates.

This assumption is also known as conditional independence (Lechner 1999; Caliendo and Kopeinig 2008). It re-emphasizes that conditional on the observables, treatment participation is exogenous and orthogonal to the outcome. In this study, students with the same propensity score share similarities regarding individual, school, household and teacher characteristics. Therefore, any difference in the outcome can be attributed to the treatment participation.

Assumption 2 Overlap $0 < P(D = 1 \mid X) < 1$

The overlap assumption is also known as common support, which is crucial in the context of non-parametric PSM. This assumption ensures substantial overlap in observed characteristics between students in the treatment and control groups. Conditional on observables, there is a positive probability of matching a *treated* student with an *untreated* student. Without the fulfillment of the overlap assumption, the treatment effect estimation is not possible.

Both assumptions 1 and 2 are strong assumptions required for estimating the average treatment effect (ATE). ATE represents the treatment effect of playing after school between treated and untreated students. To estimate the average treatment effect on the treated (ATT), the assumptions can be relaxed as *Unconfoundedness for controls*: $Y(0) \perp\!\!\!\perp D|X$ and *Weak overlap*: $P(D = 1|X) < 1$. ATT represents the treatment effect of treated students had they not been treated. The weaker assumptions are sufficient for ATT estimation since we only need to construct their counterparts for the treated group (Caliendo and Kopeinig 2008).

In this study, we are interested in examining the treatment effect for treated students and any changes in the absence of treatment since the playing after school is by nature voluntary among elementary school students. It is not our main purpose to promote the physical activities after school but to learn the effects of doing it. Investigation targeted at treated students who participated voluntarily would facilitate our understanding of the impact of playing after school. Both ATT and ATE estimates deliver empirical implications and we believe ATT estimates are more policy relevant in the context of this study. Thus, ATT is our measure of interest discussed in Section 4. We also present ATE estimates in the supplemental material. In sum, the ATT and ATE estimates remain consistent in terms of the direction of the estimates.

2.3. Matching algorithms

To obtain robust results, we utilize different matching algorithms including nearest neighbor matching (NNM), caliper and radius matching (CRM) and kernel matching (KM) (Heckman, Ichimura, and Todd 1997; Heckman, Ichimura, and Todd 1998; Caliendo and Kopeinig 2008; Imbens 2015).

The NNM algorithm matches treated students with their counterparts with the closest propensity score. The CRM algorithm matches treated students with all their counterparts within a predefined neighborhood of propensity score.[3] In contrast to the NNM and CRM algorithm that utilize a limited number of counterparts in the control group, the KM algorithm makes use of all the students in the control group to construct a counterfactual by assigning a kernel weight to each student. The matching algorithm selection involves a trade-off between bias and efficiency of the estimates. All the above-mentioned algorithms are used to check the robustness of the results. Moreover, a bootstrap process is applied in the estimation to obtain robust standard errors (Bai 2013).

3. Data

3.1. Survey

Our data comes from the 2011 TIMSS.[4] This survey is conducted every four years by the International Study Center, Lynch School of Education, Boston College, and the International Association for the Evaluation of Educational Achievement. Students from participating schools complete questionnaires about their family resources, personal studying habits, and attitudes towards school. Meanwhile, the school and teacher surveys are distributed to principals and teachers separately. Information about teaching facilities, computer resources, and school–parent interactions are also collected. Demographic information of teachers and their work experience are collected in the teacher survey.

In total, there are 369 schools, 767 teachers and 15,061 students included in our analysis. Please refer to Table 2 for more details about the sample. The average age of the students is 10 years. Approximately 50.4% of participating students are female. Non-Hispanic Whites (hereinafter referred to as Whites) account for almost half of participating students. Non-Hispanic Blacks (hereinafter referred to as Blacks), Hispanics and Asians are about 11%, 26% and 4% of the participating students, respectively.

Approximately 41% of participating schools are characterized by a large percentage (more than 50%) of students from economically disadvantaged families. Nearly half of the schools are in urban or suburban areas, and about 41% of them are in medium sized cities or more remote rural areas. Over 85% of schools are public schools and only about 2% are private schools or charter schools. On average, teachers have more than 27 years of teaching experience. There are cases of

Table 2. Summary of descriptive statistics.

Student	Observations	15,061
	Average age	10
	Gender: female	50.36%
	Race/ethnicity[a]	
	Non-Hispanic White	49.37%
	Non-Hispanic Black	11.39%
	Hispanic	25.70%
	Asian	4.24%
	Multiracial and other	7.34%
School	Observations	369
	Students from economically disadvantaged homes[b]	
	0–25%	29.11%
	26–50%	20.50%
	More than 50%	40.58%
	Population[c]	
	More than 500,000 people	12.02%
	100,001–500,000 people	17.16%
	100,000 people or fewer	59.84%
	Locality[d]	
	Urban and suburban	48.60%
	Medium size city	15.95%
	Small town and remote rural	25.52%
	Average income level of the school's immediate area[e]	
	High	6.49%
	Medium	47.89%
	Low	35.20%
	Type of school[f]	
	Public	85.42%
	Private	1.46%
	Charter	0.94%
Teacher	Observations	767
	Gender: female	74.41%
	Years of teaching experience	27

[a]1.96% of the students did not provide answers to this question.
[b]9.81% of the schools did not provide answers to this question.
[c]10.98% of the schools did not provide answers to this question.
[d]9.93% of the schools did not provide answers to this question.
[e]10.42% of the schools did not provide answers to this question.
[f]10.22% of the schools did not provide answers to this question. And 1.96% of schools belong to other types such as special education or vocational school.

missing data for the above-mentioned variables in the school and student surveys. The percentages of missing data are indicated in the footnote of Table 2.

The math and science test scores from TIMSS are used as measures for academic performance of fourth grade students. Test scores in the original survey are calculated using five plausible values according to the item response theory (Mullis et al. 2012; Martin et al. 2012). Each of the five values is reported on a scale from 0 to 1000 points. To fully evaluate the effects of academic performance, the average of the five values in the respective subject is used as the final test score for math and science. We present the summary statistics of math and science scores for the overall sample, and by gender and racial/ethnic groups in Table 3. The scores range from 270 to 770 points with an average score of 541.5 and 543.2 points and the standard deviation of 72.5 and 74.8 in math and science, respectively. Male students have higher scores than female students. White students have higher scores than Hispanic and Black students.

3.2. Treatment variable

The treatment 'playing after school' is a dummy variable and constructed based on two questions in the student survey: 'Do you play on a sports team outside of school?' and 'Do you belong to a club

Table 3. Summary statistics of test scores.

	Math		Science	
	Score mean	Std. dev	Score mean	Std. dev
Overall sample ($n = 15{,}061$)	541.504	72.495	543.233	74.831
Females ($n = 7585$)	538.324	69.885	539.315	72.348
Males ($n = 7476$)	544.732	74.917	547.207	77.071
Whites ($n = 7436$)	561.417	65.329	569.083	64.887
Hispanics ($n = 3871$)	520.680	68.755	515.400	71.420
Blacks ($n = 1715$)	491.017	65.717	491.171	68.090
Asians ($n = 639$)	591.337	68.440	574.575	69.773

outside of school (like Girl Scouts, 4-H, or Boys and Girls Club)?' As discussed in Section 1, participating in either of these two activities is considered as being treated. We define 'playing after school' as 1 if the student's answer is 'Yes' to either one of the two questions above; otherwise the treatment dummy is 0.

3.3. Channel variable

To investigate the causal link channel through parental support, the models are re-estimated separately by the level of parental support. It is hypothesized that students with high level of parental support achieve stronger effects of playing after school (i.e. higher test scores) given the evidence of the parental role in the current literature (Dunn, Kinney, and Hofferth 2003). Parental support is defined based on two behavioral questions on the parent's survey: whether parent makes sure that children set aside time to do their homework and supervise the children's homework. Students are classified into the group with high level of parental support if their parents do both, otherwise students belong to the group with low level of parental support.

4. Empirical results

4.1. Test of the assumptions

First, a balance test is performed by comparing the means of the covariates between treated and untreated students. Figure 1 is the visual representation of the test result. The variables on the *Y* axis are the matching variables. The vertical line in the graph denotes zero mean-difference in the matching variables. The graph indicates that after matching, there are no significant differences in the observed characteristics between students in the treatment and control groups.

Secondly, we assess the *Overlap* assumption by showing the density of the propensity score of treated and untreated students in Figure 2. A visual inspection demonstrates a large overlap of the density between students in the treatment and the control group. It also implies that for students who play after school, we find their counterparts who do not play after school.

4.2. Estimated effects

We present ATT estimates of playing after school in Table 4. From left to right, each column shows the effect on math and science test scores using the NNM, CRM and KM algorithm, respectively. Bootstrapped standard errors based on 200 iterations are provided in parentheses below the estimates. For the overall sample, there is compelling evidence of positive effects of playing after school on math and science test scores. The effects on math scores range from 6.60 to 6.75 depending on the matching algorithm. In other words, students who play after school have on average, at least 6.60 more points in their math scores, which represents an increase of 0.09 standard deviations from the mean math score. The estimates of the effect on science scores range from 3.31 to 4.11, which imply that students who play after school experience at least a 3.31-point increase in their science scores, which is an increase of 0.04 standard deviations from the mean science score.

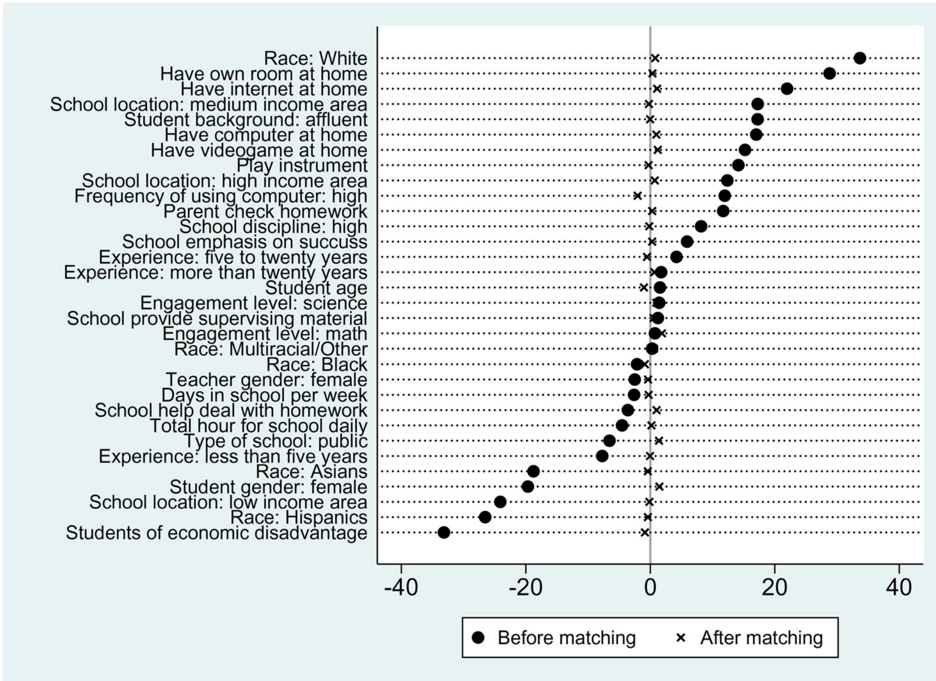

Figure 1. Balance test.

Notes: The variables on the *Y* axis are the matching variables. The vertical line in the graph denotes zero mean. The graphic representation indicates that there is no significant difference in covariates' means between the control and treatment group after matching.

Next, we estimate the model for gender and racial/ethnic subgroups. Within each subsample, the estimation is performed on the same sets of matching variables without that specific redundant matching variable. The propensity score is recalculated accordingly. In order to make sure that the PSM is feasible to all the subsamples, we perform the overlap test for each subsample and attach the graphs to the supplemental material (Figure A1). Similar to the case for the overall sample, the effect of playing after school is larger on math scores (ranging from 7.87 to 8.57, which represent

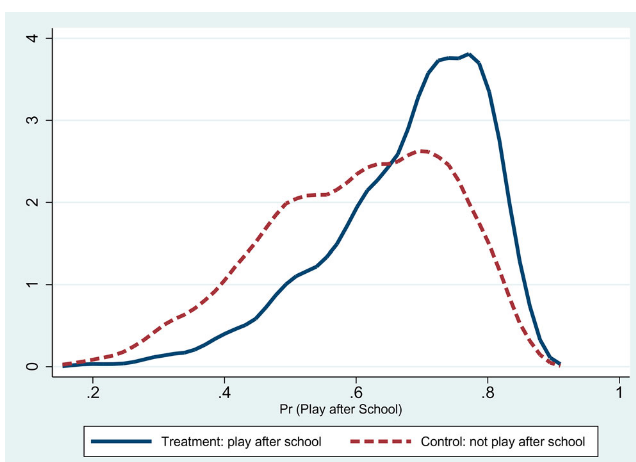

Figure 2. Overlap assumption test.

Table 4. ATT effects of playing after school for the overall sample.

	NNM		CRM		KM	
Overall	Math	Science	Math	Science	Math	Science
β	6.603***	4.107**	6.754***	3.372**	6.685***	3.310**
	(1.917)	(1.933)	(1.384)	(1.363)	(1.410)	(1.436)
N	9739	9739	9739	9739	9739	9739
Females						
β	8.566***	7.292**	7.956***	4.762**	7.868***	4.723**
	(2.718)	(2.891)	(1.880)	(1.911)	(1.811)	(2.029)
N	4935	4935	4935	4935	4935	4935
Males						
β	7.489**	4.978	5.552**	1.748	5.540**	1.765
	(3.383)	(3.161)	(2.464)	(2.323)	(2.173)	(2.136)
N	4804	4804	4804	4804	4804	4804
Whites						
β	13.975***	11.718***	12.026***	8.361***	12.060***	8.406***
	(2.969)	(2.745)	(2.152)	(2.118)	(2.113)	(2.027)
N	5010	5010	5010	5010	5010	5010
Hispanics						
β	−5.064	−7.750**	−4.844**	−5.667**	−4.840*	−5.737**
	(3.929)	(3.923)	(2.359)	(2.659)	(2.513)	(2.726)
N	2492	2492	2492	2492	2492	2492
Blacks						
β	2.687	0.042	−3.383	−6.379	−3.458	−6.523
	(6.071)	(6.995)	(3.936)	(4.735)	(4.132)	(4.151)
N	1058	1058	1058	1058	1058	1058

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
*$p < .1$.
**$p < .05$.
***$p < .01$.

an increase of 0.11 to 0.12 standard deviations from the mean math score) than on science scores (ranging from 4.72 to 7.29, which represent an increase of 0.07 to 0.10 standard deviations from the mean science score) among female students. Compared to female students, male students only experience an increase in math scores. Moreover, the magnitude of the effects on math scores is smaller for male students than for female students. For male students, math scores increase in the range of 5.54–7.49, which represent an increase of 0.07–0.10 standard deviations from the mean math score. Given these numbers, it is still not clear whether the effects between male and female students are significantly different. We conduct a chi-squared test to check for the equality of the gender estimates. The test shows that the effects on math and science scores between male and female students are not significantly different ($p = .62$ for math and $p = .46$ for science).

Regarding racial and ethnic heterogeneity, significant positive effects on both math and science scores are found among Whites. The estimates of the effect on math scores range from 12.03 to 13.98 (which represent an increase of 0.18–0.21 standard deviations from the mean math score) while the estimates of the effect on science scores range from 8.36 to 11.72 (which represent an increase of 0.13–0.18 standard deviations from the mean science score). There is no significant effect of playing after school on math or science scores among Blacks. For Hispanics, there are negative effects on math scores (i.e. −4.84) with the CRM and KM algorithms and on science test scores (ranging from −5.67 to −7.75) with all three algorithms. These numbers suggest a decrease of 0.07 standard deviations from the mean math score, and 0.08–0.11 standard deviations from the mean science score. In addition, Chi-squared tests indicate that the effects on math and science scores among Whites and Blacks, and Whites and Hispanics are significantly different ($p < .05$ for both math and science).

Panel A and panel B in Table 5 report the ATT estimates of playing after school for two subgroups of students with high and low level of parental support, respectively. We attach the overlap test graphs to the supplemental material (Figure A2). In panel A, the positive effects of playing after school are larger than those for the overall sample. This finding suggests that students who play

Table 5. ATT effects based on two levels of parental support.

	NNM		CRM		KM	
	Math	Science	Math	Science	Math	Science
High level of parental support						
β	9.910***	6.547***	7.999***	5.454***	7.951***	5.434***
	(2.611)	(2.487)	(1.803)	(1.832)	(1.631)	(1.798)
N	6374	6374	6374	6374	6374	6374
Low level of parental support						
β	5.801	2.614	5.088**	0.040	5.061**	0.006
	(3.550)	(3.736)	(2.218)	(2.611)	(2.509)	(2.785)
N	3361	3361	3361	3361	3361	3361

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
*$p < .1$.
**$p < .05$.
***$p < .01$.

after school with greater parental support have higher test scores in both math (from 7.95 to 9.91) and science (from 5.43 to 6.55) test scores. In panel B, the positive effects found for the overall sample almost disappear. There are positive effects of playing after school on math using the CRM and KM algorithms, but no effects on science scores. In addition, the magnitude of the effects on math scores (from 5.06 to 5.09) are smaller compared to those shown in panel A.

We attach the estimates from ATE and OLS regression to the supplemental material (Tables A1–A4). In a similar way, we present the results for the overall sample and two subgroups in sequence. In general, the ATE estimates follow the same direction and pattern relative to those of ATT. For example, the estimates from the overall sample suggest a positive effect of playing after school on math scores. There is also evidence indicating that this positive effect is significant among Whites, but not among Blacks or Hispanics. A major difference lies in the magnitude of the effects, i.e. the estimates of ATE are relatively small compared to those of ATT. It is not surprising since ATT captures the effects for those who voluntarily play after school, but ATE indicates the effects comparing those who voluntarily play after school and those who do not. The OLS estimates are not the same with the ATT estimates, but the direction of the effects and significance level are consistent. The consistency between OLS estimates and treatment effect estimates implies that the selection issue is not severe in this study after controlling for a rich set of covariates.

4.3. Placebo test

To check the robustness of the results, we incorporate a placebo test. One concern of the PSM approach is that there may be unobserved omitted variables in the error term that correlate with the matching variables. If this is the case, the coefficient of the matching variables may show statistical significance. Therefore, we use the birth month of students as the outcome variable as a placebo test, which is purely random and exogenous. The results are shown in Table 6. As expected, there is no significant treatment effect of playing after school on the student's birth month.

5. Discussion

5.1. Effects among gender and race/ethnicity subgroups

The chi-squared test results do not suggest any difference in the effects of playing after school by gender. Although previous literature documents higher beneficial effects for adolescent female students than male students from athletic involvement and misconduct, our results differ for younger students in our study (Miller et al. 2005). Current studies identify positive correlations between physical activities and self-esteem among 12 year old elementary school students (Tremblay, Inman, and Willms 2000). Furthermore, self-esteem of students is closely related to their self-evaluation, self-

Table 6. Placebo test.

	NNM	CRM	KM
General			
β	0.021	0.019	0.019
	(0.108)	(0.081)	(0.079)
N	9676	9676	9676
Females			
β	−0.205	−0.124	−0.124
	(0.168)	(0.105)	(0.112)
N	4900	4900	4900
Males			
β	0.247	0.155	0.154
	(0.176)	(0.117)	(0.118)
N	4776	4776	4776
Whites			
β	0.018	0.117	0.116
	(0.168)	(0.120)	(0.115)
N	4979	4979	4979
Hispanics			
β	0.185	0.087	0.089
	(0.220)	(0.145)	(0.148)
N	2487	2487	2487
Blacks			
β	−0.414	−0.158	−0.162
	(0.333)	(0.237)	(0.249)
N	1037	1037	1037

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
*$p < .1$.
**$p < .05$.
***$p < .01$.

perception and academic performance (Booth and Gerard 2011). There is no compelling evidence showing that physical activity participation influences male and female students through self-esteem differently. Other mechanisms might work in this context as well, but there are very limited studies related to this issue. In this regard, future studies might examine other potential mechanisms and investigate heterogeneous age effects of playing after school on academic studies by gender.

The effects of playing after school on math and science test scores suggest strong heterogeneity among racial and ethnic groups. In general, the treatment effects are positive among Whites, weakly negative among Hispanics, and insignificant among Blacks.

There is evidence that the percentage of Blacks and Hispanics that participate in Club/Scouts is lower than Whites (Pew Research Center 2015). Another study suggests a higher percentage of White students engaging in physical activities compared to Black and Hispanic students (Sagas and Cunningham 2014). There main reason for the discrepancy of participation in after school activities is the rising cost to participate in sports teams (Wong 2015). As shown in Pedersen and Seidman (2005), students from a low SES are 25–33% less likely to participate in sports after school. It is reasonable to assume that a larger proportion of Black and Hispanic students fall into this group. Therefore, we believe that compared to White students, Black and Hispanic students are less involved in structured and organized activities as discussed in this study. In this regard, the treatment of playing after school might be less applicable to Black and Hispanic students and future research could also consider unorganized activities.

5.2. A plausible channel through parental support to enhance (reduce) the effects

Further analysis using the subgroups of students receiving high level of parental support and low level of parental support allows us to evaluate whether the effect on academic performance depends on different levels of parental support. High (low) level of parental support is associated with positive (weak or no) effects of playing after school on academic performance of the children.

Broadly speaking, parental support is one form of social support that influences physical activity participation in children. Other social support factors include environmental and interpersonal factors (Allen 2003; Beets et al. 2006; Humbert et al. 2006). In recent literature, parental support has been recognized as a primary influence on youth physical activity and related behaviors (Beets, Cardinal, and Alderman 2010; Trost and Loprinzi 2011). Parental influence on physical activities has been studied and discussed through the establishment of role models, family cohesion, and logistic support, to name a few (Hoefer et al. 2001; Davison, Cutting, and Birch 2003; Gustafson and Rhodes 2006). More systematically, parental support has been identified as acting via tangible and intangible mechanisms (Beets, Cardinal, and Alderman 2010). Beets, Cardinal, and Alderman (2010) consider tangible parental support as instrumental involvement, such as paying membership fees and offering logistics; or conditional, such as doing physical activities with their children. Meanwhile, intangible social support can be motivational, such as encouragement and praise; or informational, such as talking about the advantages of doing physical activities.

In this study, parental support focuses more on helping children to efficiently manage their time after school. Recall our definition of parental support entails parents making sure their children set aside time to do their homework and actively supervise it. Parental involvement improves the efficiency of their children's time allocation. The time management channel works as an alternative avenue to tangible parental support in addition to offering logistic or financial support. In turn, students with higher level of parental support may achieve better test scores through better time management. We believe this finding provides a new perspective for evaluating the influence and role of the parents when discussing the relationship between playing after school and consequential effects on academic performance.

6. Conclusion

This paper uses a PSM approach to estimate the treatment effects of playing after school on math and science scores. Our results indicate that playing after school increases math and science test scores for fourth grade students. The results also suggest heterogeneous effects by racial/ethnic groups. We present evidence of parental support as a channel to enhance (or reduce) the effects of playing after school. The findings of this study shed light on future after school physical activity intervention program design by incorporating parental support as a key factor. The findings are also instructive for schools to offer guidance to parents regarding support for after school activities of their children. Furthermore, special attention should be given to Hispanics and Blacks due to their relatively lower level of participation in organized and structured after school activities.

Notes

1. Other literature shows that health relevant issues are related with children aged 6–11 (see Ogden et al. 2002; Yawn et al. 2015).
2. There is evidence indicating that Girl's Club/Girl's Scout or Boy's Club involve certain levels of physical activities in academic studies, according to scientific reports and press releases from health science organizations (Lipscomb 2007; Ornelas and Rosenkranz 2009; Rosenkranz, Behrens, and Dzewaltowski 2010; ACSM 2016; Girl Scouts of the USA 2016; GSOFCT 2016; Kansas State University 2009; BGCA 2016).
3. The radius is set to 0.05 in this study.
4. TIMSS 2011 is the latest survey available.

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