THREE ESSAYS ON ECONOMIC EVALUATION OF HEALTH INTERVENTION PROGRAMS AND HEALTH POLICY

A Dissertation

by

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ABSTRACT

This dissertation is mainly focusing on an economic evaluation of a childhood obesity intervention program, after school physical activities and a nationwide social health care program. The analysis is conducted within three main essays. The purpose of the first essay is to estimate peer effects on third grade students' BMI and to investigate the social and physiological explanations for such effects. The BMI of students from a childhood obesity intervention program (N=573) is used to assess peer effects on students' BMI by identification of endogenous social effects. We apply IV regression to account for this endogenous effects. Strong peer effects are found for the overall sample, females and males ($p<.1$). However, when classifying students into improvement versus non-improvement groups, the peer effect is only found among females categorized in the improvement group (β =1.472) and males in the non-improvement group (β= 1.176). Thus in general, peer effects are found for students aged 8-11, with sex differences in the psychological and social behavioral motivations.

In the second essay, we exploit the data from the Trends in International Mathematics and Science Study (TIMSS) 2011 to evaluate the effect of playing after school on academic performance by using a propensity score matching approach. We highlight that in addition to intrinsic characteristics of students, the extent to which after school activities affect academic performance depends on extrinsic factors such as parental involvement. In order to capture the heterogeneous effects of playing after school, we analyze the effect by separating the overall sample according to whether

parents check their children's homework and set specific times for after school homework. We further uncover heterogeneous effects of playing after school for different levels of parental involvement and supervision. The results show that playing after school significantly increases math and science test scores of students by 7.9 points and 4.2 points respectively. Moreover, this positive effect is stronger among students with greater parental involvement and supervision, but weaker or nonexistent among students with less parental involvement and supervision.

The third essay fills the gap in the literature by examining the long-term causal effects of Medicaid enrollment on high school and college completion through a regression discontinuity design that exploits an eligibility discontinuity created by the Medicaid expansion of 1990. Using the American Community Survey data, we present evidence that Medicaid enrollment decreased high school completion rates by 3.6 percentage points (using local linear regression and IK bandwidth selector). However, we find little evidence of adverse impact of Medicaid on college completion. We also find heterogeneous effects by race/ethnicity. While Medicaid has no significant impact on educational achievement of blacks or Asian, Hispanics are negatively affected by Medicaid on both high school and college completion.

DEDICATION

To my family and friends

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NOMENCLATURE

ACS	American Community Survey
ATE	Average Treatment Effect
ATT	Average Treatment on the Treated
BMI	Body Mass Index
CCT	Calonico, Cattaneo and Titiunik
CHIP	Children's Health Insurance Program
CRM	Caliper and Radius Matching
IK	Imbens and Kalyanaraman
IV	Instrumental Variables
KM	Kernel Matching
NNM	Nearest Neighbor Matching
OBRA	Omnibus Budget Reconciliation Act
PSM	Propensity Score Matching
RD	Regression Discontinuity
TEA	Texas Education Agency
TGEG	Texas Grow! Eat! and Go!
TIMSS	Trends in International Mathematics and Science Study

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1 INTRODUCTION

"The first wealth is health." - Ralph Waldo Emerson.

The importance of health and health related issues cannot be overemphasized in contemporary society. After all, the efficient allocation of medical resources is critical to the overall well-being of a society. On an individual level, even a small change to a health care policy can affect a person's health behavior and outcome, financial decision, and attitude towards work and other aspects of life.

Education plays an important role in a nation's innovation, development and future; and a child's educational achievement or academic performance is generally associated with his or her health condition (Trudeau and Shephard 2008, Hollar et al. 2010a, Dwyer et al. 2001). The health condition of a child is not only affected by his or her lifestyle such as participating in physical activities but also by policy factors such as the health care program in which they enroll. For instance, a social health care program could improve the health condition of enrollees by providing them with access to health care; on the other hand, the eligibility (usually related to low levels of family income) requirement might trap enrollees in a disadvantaged situation, which in turn may negatively influence their attitude towards work and education. Due to these potentially conflicting influences, researchers are interested in more than just knowing the immediate effects of one policy or intervention. Scholars put more emphasis in exploring longer term effects together with immediate effects, and also investigating in possible underlying behavioral explanations or mechanisms.

The main objective of this dissertation is to evaluate the effects of a health care policy, a health intervention program, and a health-related behavior by employing causal effects analysis methods including instrumental variables approach (IV), propensity score matching (PSM) and regression discontinuity design (RD). In order to accomplish the main objective, three essays are presented to address three specific settings: 1) estimating peer effects from a school based childhood obesity intervention program, Texas Grow! Eat! and Go! (TGEG); 2) investigating the influence of after school physical activities on academic performances of fourth grade elementary school students using 2011 Trends in International Mathematics and Science Study (TIMSS); and 3) examining the impact of Medicaid enrollment on high school and college completion rates using 2014 American Community Survey (ACS) data.

In the first essay, I investigate peer effects from a childhood obesity intervention program. The reason I am interested in this topic lies in the severity of obesity among children. A large nationwide study identified that approximately 12.5 million (representing 17% of the US population) children and adolescents in the US from the age of 2 to 19 were considered obese (Ogden and Statistics 2012). The obesity rates in the US among children and adolescents have increased by three times since the 1980s across the US (Ogden and Statistics 2012). The cost of childhood obesity is considered to be one of the major economic burdens for the nation (Withrow and Alter 2011). The annual cost associated with increasing BMI among children and adolescents is approximately $14.1 billion, including costs of emergency room, prescription drugs and outpatient visits (Trasande and Chatterjee 2009).

Special attention has been given to children coming from low income families since they are at higher risk of becoming obese. Children from low income families have less access to healthy foods and physical exercise facilities in their neighborhoods, and have more frequent visits to fast food restaurants near their schools (Andreyeva et al. 2010, Drewnowski 2009, Fleischhacker et al. 2011, Sallis and Glanz 2009).

I explore peer effects on students' BMI using survey data from the intervention program of TGEG. The goal of the TGEG program is to help reduce childhood obesity among third grade students within Texas. I am particularly concerned about social interactions and peer influence among students. Obesity proves to be one of the most challenging health issues especially among children and adolescents due to their vulnerability (Cohen-Cole and Fletcher 2008). During this stage of life, children are developing their life habits and self-esteem partially based on interactions with their peers in their "neighboring environment", such as schools, community, and after school classes. Building up a full understanding of effects of peer influences on an individual student's BMI according to sex and his/her natural growth is critical. The majority of previous literature evaluates peer effects using cross-sectional data, in which certain information about children's natural growth is not accounted for (Fortin and Yazbeck 2011, Trogdon et al. 2008). More specially, children in the overweight and obese category have social interactions and self-awareness that differs from children in the normal weight category. Using pre and post intervention data, I capture the heterogeneity in peer effects in two BMI categorization groups, *improvement* group vs *non-improvement* group.

To account for the endogeneity arising from peer interaction, I apply walking exercises of peers' parents as an instrument variable for peers' BMI. The most commonly used IV in similar studies is parents' BMI in order to account for the genetic relation between parents and their children. The IV used in this study reflects not only the genetic relation but also the "environmental" influence between parents and children, i.e. parents' physical activities will influence their children's BMI. The relevance of this instrument is supported both by empirical evidence of the relationship between parents physical exercises and children's BMI, and statistical tests during the estimation (Fuemmeler et al. 2011, Zecevic et al. 2010, Erkelenz et al. 2014).

The results suggest heterogeneity in peer effects among different groups by sex and BMI categorization. More specifically, male students are more likely to be influenced by their interactions with peer friends towards the direction of unhealthy BMI categorization; female students, on the contrary, are more likely to be influenced by their interactions with peer friends towards the direction of healthy BMI categorization. These findings broaden the existing knowledge of peer effects and provide valuable implications for future intervention program design.

The goal of the second essay is to provide a general picture of whether or not and to what extent doing physical activities after school improves the academic performance of elementary school students. Compared to normal weight children, obese children are more likely to have cardiovascular disease, heart disease, asthma, and diabetes (Freedman et al. 2007, Kavey et al. 2003, Wolk et al. 2003). In addition to health related risks, obese children normally have lower cognitive ability and lower self-esteem, which in turn may lead to poor performance in academic studies and discipline records (Datar et al. 2004, Hollar et al. 2010b). In this essay, I specifically focus on the effect of playing after school on math and science test scores of fourth grade students.

To account for the self-selection issue in the study, e.g. the students who are physically active might be more energetic and also put more effort in academic studies as well, I employ a propensity score matching approach. By estimating the propensity score (using a probit model), which represents the probability of an individual student of playing after school (i.e. in the treatment group), I match students who play after school (i.e. in the treatment group) with students who do not play after school (i.e. in the control group) using different matching algorithms. Then the treatment assignment (whether or not the student plays after school) of students with the same propensity score is exogenously determined. All variables that determine whether students play after school are included in the probit model.

The results show that playing after school significantly increases math and science test scores of fourth grade students. I incorporate parental involvement as one more dimension in the analysis, given the fact that parents influence whether their children play after school and the quality of playing after school under their guidance and support. Therefore, I further estimate the effects according to different levels of parental involvement and supervision. Moreover, I find that greater parental involvement and supervision is associated with stronger positive effects of playing after school on test scores, but less parental involvement and supervision is associated with weaker or nonexistent effects on test scores.

The third essay investigates the long term effects of Medicaid enrollment on educational attainment. There are consistent research findings showing improved health outcomes and increased heath care resulting from certain health insurance programs. However, as argued by Murray (1984) in his seminal work *Losing Ground*, short term welfare programs crowd out incentives to work and erode human capital of enrollees in the long run. Murray's work is significant because it looks into the dark side of welfare programs and explores more efficient ways to help the disadvantaged. For decades, empirical studies have documented the impacts of disability insurance programs on labor force participation. See for example by Chen and Van der Klaauw (2008), French and Song (2014), Maestas et al. (2013), von Wächter et al. (2011), and David (2015). Most of above mentioned studies provide evidence showing that participation in disability insurance programs reduces employment.

It is not clear whether Medicaid has a similar effect on enrollees as those of disability insurance programs. As such, the impact of Medicaid recently has gained the attention and interest of scholars (Finkelstein et al. 2011, Strumpf 2011, Baicker et al. 2013, DeLeire et al. 2013). I focus the empirical analysis on a Medicaid expansion for several reasons. First of all, Medicaid covers a larger population compared to disability insurance programs. Therefore, Medicaid has more profound policy implications accordingly. Second, I specifically concentrate on educational attainment for children who enrolled in Medicaid. To the best of my knowledge, this is the first study assessing the effect of Medicaid on high school completion rates. By exploiting a policy discontinuity created by the Omnibus Budget Reconciliation Act of 1990 (OBRA 1990), I apply the regression discontinuity design to analyze the effect of Medicaid on educational attainment. More specifically, OBRA 1990 regulates that children who were born after October 1983 were qualified to enroll in Medicaid, but children born before October 1983 were not, even if facing the same socioeconomic conditions. Assuming that other factors of children were smooth across the cutoff line (October 1983), any discontinuity in the outcome variable is believed to be caused by the discontinuity in the policy (i.e. eligibility). The results suggest a negative effect of Medicaid enrollment on high school completion rates. I believe that this conclusion is consistent with Murray's work. Due to the limitation of the ACS data, I could not provide a detailed explanation of the mechanism through which Medicaid enrollment affects the high school completing rate of enrollees. Possible explanations may be through influencing family disposal income, parents' labor market activities, or parents' devotion to their children's education after 1990. I put forward some potential explanations for the negative effects. First of all, parents of enrolled families might not have paid the same attention to the physical condition of their children as they did before, presumably because they know that even if their children had a health problem they would be covered. This situation is commonly observed in health insurance markets and it is widely known in economics as *moral hazard*. Second, parents of enrolled families might not have enough incentives to work. This attitude might set up a negative example to their children and gradually influence their general attitude towards work and school.

The rest of the dissertation is organized as follows: chapter 2 examines the peer effects of childhood obesity using TGEG data. Chapter 3 evaluates the effects of playing after school using a propensity score matching approach. Chapter 4 investigates the effect of Medicaid on the high school completion rate and the college completion rate and the last chapter concludes.

2 PEER EFFECTS ON CHILDHOOD OBESITY FROM AN INTERVENTION PROGRAM*

2.1 Introduction

Currently, childhood obesity is one of the most challenging health issues in the United States. Approximately 12.7 million children and adolescents from the age of 2 to 19 years within the United States are obese (Ogden et al. 2014). Childhood obesity rates have more than tripled during the last 4 decades, from approximately 5% in 1971 to 17% in 2010 (May et al. 2013). Nationwide, Texas ranks 10th among US states regarding obesity rates for children aged 10 to 17 (Valls 2012).

Although some variations in the definition exist, for this article, *peer effects* refer to the influence exerted on individual students from peers, such as friends, who are also exposed to the same environment, or to individuals of the same age (Hoxby 2000). Recent literature highlights peer effects on health-related behavior among different age groups with particular attention to adolescents' unhealthy behavior such as smoking and physical fitness problems (Fortin and Yazbeck 2011, Asirvatham et al. 2014, Hoxby 2000, Nakajima 2007).

Adolescents are of special interest due to their vulnerability at a period where lifestyles and self-consciousness are becoming established (Davis and Franzoi 1991). Peer effects on BMI or prevalence of childhood obesity have been identified in previous

* Reprinted with permission from "Peer Effects on Childhood Obesity from an Intervention Program" by Li Y, Palma MA, Towne SD Jr, Warren JL, & Ory MG. 2016. *Health Behavior and Policy Review* 3(4):323-335.

studies using national health surveys, e.g. The Framingham Heart Study, or local health datasets, e.g. Arkansas public schools (Asirvatham et al. 2014, Christakis and Fowler 2007, Datar et al. 2004). These studies indicate that peer effects analyses are dependent on factors such as the definition of the peers, the estimation method, and the correction for potential endogeneity, which are more than just a statistical correlation between individuals and peer groups (Asirvatham et al. 2014).

A major research gap exists given the fact that there are few studies investigating peer effects under the context of BMI categorization change over time, which is a result of children's behavioral changes. A primary unanswered research question is how to analyze the peer effect together with children' healthy behavior while accounting for their natural growth. Little is known about the underlying framework of peer effects in terms of social preference and social identity within this context.

A specific challenge in obesity research is to ascertain the peer effect given that all students are exposed to the same school environment. Previous studies identified social interaction as one of the determinants that influence youth's behavior and health outcomes (Powell et al. 2005). The actions of one's peers can influence individual decision making in a number of ways, and therefore, influence health-related behaviors and outcomes (Powell et al. 2005, Manski 1993, Brock and Durlauf 2001, Glaeser and Scheinkman 2001). The effects of experiential learning on healthy food choices, dietary habits and encouragement for physical activities at school might motivate similar behavior among students, which in turn, influence BMI. In this case, an individual student's BMI change may be the result of behavioral changes of the individual students themselves, influence from behavioral changes of the peer group, or a combination of both. The effect of BMI of a peer group on an individual's BMI is what we are identifying for a causal interpretation.

Similar trends for BMI changes among students likely result from unobserved characteristics such as family backgrounds. Parents with low family income levels has a predisposition for low physical activity or probably send their children to the same school within certain area, which may create selection bias (Powell et al. 2005). Therefore, children from low-income families often face difficulties related to limited access to healthy and affordable food (Andreyeva et al. 2010, Drewnowski 2009), high frequent visits to near-to-school fast-food restaurants (Fleischhacker et al. 2011), and less access to physical exercise facilities in their neighborhoods (Sallis and Glanz 2009). These research findings suggest the possibility that similar behavior or physical fitness measures of an individual student and his or her peer group may arise from similar family characteristics, or similar unhealthy lifestyles resulting from the neighborhood environment. These effects might not be directly working on individuals, but has an unobserved effects on the individuals' behavior.

Additionally, there is also a mutual peer effect of those within the same social network, which may lead to potential simultaneous bias (Manski 1993). Such endogeneity effects could have biased the study results if not appropriately accounted for by the research design.

Our research aims at examining the relationships between peer effects, sex groups and BMI trend categorization groups when students' improved behavior creates a new *obesogenic* environment (less or more), utilizing data gathered from *Texas Eat! Grow! and Go!* (TGEG), a school-based childhood intervention that focuses on gardening and physical activity education.

The purpose of this study was not to examine the effect of the intervention program, but to explore the underlying psychological and behavioral interpretation of peer effects based on social group identity theory and social network affiliation by sex. This paper adds to the literature in two important ways. First, a large body of literature investigates peer effects on adolescent obesity using different instrumental variables (IV) to account for endogeneity. An IV must be closely related to endogenous variables, but unrelated with the dependent variable. The only way that IV affects the dependent variable is through the endogenous variable. For example, peer's birth weight, or their parents' self-reported health related measures are used as a proxy for peer's BMI or weight, considering biological and environmental relations (Trogdon et al. 2008). In this analysis, a new IV, number of days that parents walk for at least 10 minutes per week, is employed to account for the endogeneity of peer effects on students' BMI. The validity of this IV is based on research findings in health economics that examine relations between parental physical activities, parental-children health related behavior and children's BMI (Fuemmeler et al. 2011, Zecevic et al. 2010, Erkelenz et al. 2014). These findings show that students with physically-active parents have lower BMI percentile values than those with physically-inactive parents (Erkelenz et al. 2014). The association between parent physical exercise and student BMI serves as the theoretic support for the validity of the IV.

Second, previous studies typically conduct rudimentary analyses across sex and ethnic groups. We analyze the sex impact on peer effects for two BMI trend categorization groups (*improvement vs non-improvement*), and also explore the underlying psychological and behavioral interpretations. The theory of social identity suggests that building up the social identity for any individual involves categorization, identification, and comparison (Tajfel et al. 1971, Chen and Li 2009, Tajfel and Turner 1979). Accordingly, boys and girls demonstrate different ways of interaction regarding identification and comparison (Tajfel et al. 1971, Chen and Li 2009, Tajfel and Turner 1979). Evidence shows that boys care about athletic participation more than girls and the close relationship among boys would be reinforced by participation in sports activities (Benenson and Benarroch 1998, Trost et al. 2002, Zarbatany et al. 2000); meanwhile, girls may care more about popularity and attractiveness compared to boys (Benenson and Benarroch 1998, Trost et al. 2002).

As students' BMI categorization groups change over time, peer effects on BMI might or might not vary. A systematic review evaluates physical attractiveness and its influence on peer interactions among children, and shows that physically attractive children demonstrate more positive general behavior compared to unattractive children based on fitness-related evolutionary theory and socialization theory (Langlois et al. 2000). Another study on children's peer culture shows that children would spend a lot of effort including time and energy to obtain and maintain access to certain groups with desired characteristics (Corsaro and Eder 1990). It is also identified that physically attractive children get preferential treatment (Langlois et al. 2000). It might be natural to assume that children within a desirable BMI category (or body image) would interact more with children with similar characteristics and influence each other in a positive way. The findings of our analysis support that physical activities contribute to maintaining or switching students to normal weight BMI category among third grade school children, and show that the underlying sex differences in terms of behavior and psychology cause distinct peer effect on BMI values within each BMI categorization group respectively.

2.2 Methods

2.2.1 Target Population

TGEG is an intervention program to help reduce childhood obesity for third grade students in Texas public elementary schools. Texas A&M AgriLife Extension Service in collaboration with Texas A&M University (TAMU) School of Public Health and University of Texas School of Public Health, Austin Regional Campus, began implementing TGEG in 2012. A total of 16 Title I schools, in which approximately over 40% of students were from low-income families, in four counties within Texas participated in this program. This population is the focus of this paper. The participation of schools was voluntary and contingent upon the contact between TGEG organizers and schools. The intervention measures include promoting physical activities among students both at school and at home, and dietary and gardening education by means of class curriculum and extracurricular activities such as working in a small garden on campus.

2.2.2 Surveys and Data Collection

Surveys for students and parents were distributed to each school at the beginning of the 2012 fall semester, which is denoted as $t1$, and at the end of 2013 spring semester, which is denoted as $t2$. Parent surveys were sent home, completed by parents and returned to schools; students always completed surveys in the class at school. TGEG program staff members distributed and collected these surveys with help from teachers. BMI of students was measured at the same time when the surveys were collected by TGEG program staff members. Survey questions reflect behavioral changes in physical activities, dietary habits, and gardening activities at school and at home, and student-parent interactions at home from $t1$ to $t2$. Sociodemographic questions are included in the parent's surveys.

2.2.3 Variables of Interest

The dependent variable was students' BMI. Covariate selection is based on the theoretical framework of the social determinants of health, which indicates that factors such as economic status, education, race and income inequality likely influence the individual's health (Viner et al. 2012, Braveman et al. 2011). The covariates selection is also based on previous research findings, which show that both eating awareness, dietary behavior and physical activity all influence individual's BMI (Barrington et al. 2012, Patrick et al. 2004, Iannotti and Wang 2013). In this study, independent variables included student and parent demographics (i.e. age, sex, education, and marital status), and behavioral variables from both the student survey and parent survey. More specifically, they include students' behavior (i.e. moderate physical activities at school, vegetable consumption, and physical activities at home), parents' behavior (i.e. vegetable provision, and demonstrating how to prepare vegetable snacks), and student-parent interactions (i.e. parents walking with their child at home). Other independent variables include teachers' encouragement for eating healthy food at school, food availability at home at the end of month, percentage of minorities in the class and percentage of students registered for the free lunch program in the class. Table 2-1 provides more details. Variables including moderate physical activities at school, vegetable consumption, and teachers' encouragement for eating healthy food at school are from the student survey, and all other variables are from the parent survey.

Sex and BMI Trend Categorization Groups. The peer effect analysis is conducted controlling for sex and BMI trend categorization groups. The classification of two BMI trend categorization groups is based on the findings from the 2011 FitnessGram data and third to fifth grade elementary school students' BMI trend. According to the 2011-2012 FitnessGram data released by the Texas Education Agency (TEA), we have grade-level BMI information for both third grade and fourth grade of 11 of the TGEG participating schools, with information for 5 TGEG schools missing. Among these schools, the percentage of students whose BMI values were classified as 'at some risk' was higher at fourth grade than third grade for at least one sex or both for all 11 schools. There were 10 schools with a higher percentage of students whose BMI values were classified as 'at high risk' at fourth grade compare to third grade for at least one sex or both. Based on this trend, there was a high risk for students' BMI increases or BMI categorization group changes when students move from third grade to fourth grade. Given this fact, we define the *BMI improvement group* as students who remained in the normal weight group for both periods, switched from any other groups to the normal weight group, or switched from the obese group to the overweight group. The *BMI non-improvement group* in this study consists of all other cases.

2.3 Econometric Model

Correctly identifying potential endogenous social effects requires specifying the composition of the reference group, and framing relations between the individual and the reference group and other independent variables that may affect the individual and the reference group simultaneously. Following Manski's work in ***Identification of Endogenous Social Effects*** (Manski 1993), the foundation for interpreting simultaneous/similar trends between the individual and the reference group is generalized as: 1) endogenous/causal effect, referring to the influence from the reference group because of the same intrinsic unobserved characteristics; 2) exogenous /contextual effect, referring to the influence from the reference group because of extrinsic characters of the reference group; and 3) correlated effects, referring to the influence from the reference group because of the same institutional environment (Trogdon et al. 2008, Manski 1993).

The econometric model employed to analyze peer effects follows Manski's identification theory (Manski 1993, 1999):

$$y_{ist} = \bar{y}_{jst} * \beta + x_{ist} * \eta + Z_{jst} * \gamma + \lambda_t + \mu_{ist} \qquad j \neq i \quad t{=}1 \text{ or } 2;$$

Table 2-1: Explanatory variables

Variable	Label	Level	Interpretation
Students Behavior			
Moderate physical activities (30 min) yesterday	Almost every day, I do moderate physical activities.	0	No
		1	Yes
Vegetables consumption yesterday	Yesterday, did you eat vegetables like potato?	0	No, I did not eat yesterday
		1	Yes, I ate yesterday
Physical activities at home per week	In the last week, how many times after school was your child physically active? For example, do sports, dance, or play outdoor games.	0	None or just once
		1	2-3 time
		2	4-5 times
		3	6 times or more
Parents Behavior			
Vegetable snack making demonstrations	Did you show your child how to make vegetable snacks last week?	0	No
Vegetables provision at home	How confident are you that you could regularly serve vegetables at each dinner?	0	Not at all or just a little
		1	Pretty confident or very confident
Student-Parent Interactions			
Days of parents child walking exercise last week	During the last week, how many days did you take a walk with your child?		
Other			
Food availability at the end of month	How often do you run out of food before the end of month?	0	Almost always
		1	Sometimes or never
Encouragement from teachers	Does your teacher like for you to be healthy?	0	Not at all
		1	Yes

y_{ist} is the BMI score of individual i in school s, at time t; $\bar{y}_{jst}$, endogenous/causal effect, is the BMI of the individual i's peer group, calculated as the average BMI of students in the peer group; "peer group" is defined as other students in the same grade assuming that they are exposed to the same school environment where they can interact through dietary education, classroom activities and physical activities (Asirvatham et al. 2014). x_{ist} is a vector of independent variables, which are discussed in the methods section, Z_{jst}, exogenous/contextual effect, which include the percentage of minorities and percentage of students registered for the free lunch program. λ_t is a time trend effect, and μ_{ist} is an individual specific error term. Similarly, the IV "number of days that parents walk at least 10 minutes per week" is calculated as the average total number of days that parents of children within the peer group walked for at least 10 minutes per week.

2.4 Results

2.4.1 BMI Changes over Time

The final sample included 734 student surveys at $t1$, 712 student surveys at $t2$; 560 pre-intervention parent surveys at $t1$ and 405 parent surveys at $t2$. Students in the sample had an average age of 8 years and 53.68% of participants (N=734) were girls. Nearly half (49.82%) of participating students were Hispanic. White, Black and Asian students accounted for 25.18%, 26.61% and 3.39% of the sample respectively. The final sample (N=573) used for analysis excluded observations with missing students' BMI data either in the timeframe $t1$ or $t2$.

Approximately 87.05% (N=363) of parents who responded to the survey were

Table 2-2: Mean BMI changes over time

Proportion	BMI at $t1$	BMI at $t2$	Difference ($t2 - t1$)	Std. Err.	95% Confidence Interval	
Overall (N=573)	19.017	19.505	0.488**	0.257	-0.993	0.017
Male (N=259)	19.252	19.645	0.392	0.394	-1.167	0.382
Female (N=314)	18.823	19.390	0.567**	0.338	-1.231	0.098

* p<.1, ** p<.05, *** p<.01

women with an average age of 36 years and 58.20% of parents (N=366) had a full time job.

The number of students in the overweight, obese and underweight groups decreased from $t1$ to $t2$, whereas the number of students in the normal weight group increased modestly from 283 to 294. The number of girls in the normal weight group increased from 159 to 167, and the number of boys in the normal weight group increased from 124 to 127. Two sample t-tests with equal variance in Table 2-2 show average BMI for all participating students' increased by 0.488 points from $t1$ or $t2$, and average BMI for girls increased by 0.567 points from $t1$ or $t2$. The average BMI for boys remained the same. Behavioral variables changes are shown in Table 2-3. Among these self-reported measures, students improved regarding daily moderate physical activities at school and doing physical activities at home, with an average mean increasing from 0.846 to 0.902 for daily moderate physical activities at school, and from 1.327 to 1.579 for doing physical activities at home. Parents improved regarding demonstrations to their children on how to prepare vegetables snacks.

Table 2-3: Behavioral variables changes over time

Variable	Mean at $t1$	Mean at $t2$	Difference ($t2 - t1$)		Std. Err
Students Behavior					
Moderate physical activities (30 min) yesterday	0.846	0.902	0.056	**	0.020
Vegetables consumption yesterday	0.546	0.489	-0.056		0.030
Physical activities at home per week	1.327	1.579	0.252	***	0.072
Parents Behavior					
Vegetable snack making demonstrations	0.319	0.442	0.123	***	0.037
Vegetables provision at home	1.707	1.669	-0.038		0.035
Student-Parent Interactions					
Days of parents child walking exercise last week	1.957	2.085	0.128		0.144
Other					
Food availability at the end of month	0.150	0.129	-0.021		0.027
Encouragement from teachers	0.954	0.947	-0.007		0.013

* p<.1, ** p<.05, *** p<.01

2.4.2 General Peer Effects on the Overall Sample

Peer effects were estimated according to the econometric model previously shown. Observations from $t1$ or $t2$ were included in the model. The validity of the IV was tested by a standard identification test. Both the F-test of excluded instruments (p<.001) after the first stage estimation and Cragg-Donald Wald F-test (F=77.396) for weak identification justified that the IV employed in this analysis was valid through the strong correlation with the endogenous variables and explaining the variation in individual BMI by its correlation with peer's BMI. The Sargan test for over identification is not included here given we have only a single endogenous variable and a single IV in this study.

Results based on the full sample, the sample of boys, the sample of girls, and non-improvement and improvement group students are shown in Table 2-4. In general, evidence indicates significant peer effects among all participating students, as shown in column 1 of Table 2-4. A one-point BMI increase in the peer group was associated with an increase of 1.015 points in the individual's BMI. Parents' education was significant in the model, which indicates individual BMIs would be 0.871 points lower if the parent had a college degree or higher compared to other students whose parent did not have a college degree.

In terms of the behavioral variables, doing physical activities at home (β=-1.292), eating vegetables (β=0.716), and parents' demonstrating how to prepare vegetable snacks (β=1.039) showed significant association with students' BMI. Among these significant factors, doing physical activities was found to be associated with students' BMI decrease. In contrast, behavior related with vegetable consumption and vegetable snack making demonstrations were associated with students' BMI increase.

2.4.3 Peer Effects by Sex and BMI Categorization Groups

Peer effects were found both among boys (β=1.017) and girls (β=0.995) and the results are shown in the second and third columns of Table 2-4. For boys, whether parents had a college degree or not was associated with a students' BMI decrease (β=-1.374). Regarding the behavioral variables, those that had a significant effect on students' BMI among boys had no effect among girls and vice versa. For example, compared to doing none or little physical activities at home, doing physical activities at home two or three times was associated with a decrease of 1.666 points of girls' BMI, but it had no effect on boys' BMI; doing physical activities more than three times at home was associated with a decrease of 1.532 points of boys' BMI, but it had no effect on girls' BMI.

We separated the sample into two groups: BMI improvement group and BMI non-improvement group. The final sample included 258 students in the non-improvement group and 315 students in the improvement group. Results are shown in the fourth and fifth columns of Table 2-4 for each group. Peer effects were identified both in the improvement group (β=1.109) and in the non-improvement group (β=0.976). The results show that for students who remained or switched to the improvement group, the individual's BMI increased 1.109 points when their peers' BMI increased one point; meanwhile for students who were in the non-improvement group, the individual's BMI increased 0.976 points. The higher peer effect in the improvement group indicated stronger favorable interactions between individuals and their peers within this group.

We further investigated peer effects across the two BMI trend categorization groups by sex, which are shown in Table 2-5. The results revealed heterogeneous peer effects across sex and BMI trend categorization groups. Interestingly, significant peer effects

Table 2-4: General peer effects on the full sample, by sex and BMI groups

	Full	Male	Female	Non-Improvement Group	Improvement Group
Peer effect	1.015***	1.017*	0.995*	0.976*	1.109***
	(0.384)	(0.537)	(0.571)	(0.505)	(0.288)
Age	0.170	0.207	0.306	0.413	-0.256
	(0.703)	(0.991)	(1.017)	(0.928)	(0.506)
Sex	0.195			0.409	-0.011
	(0.380)			(0.524)	(0.284)
Marital	-0.056	-0.914	0.423	0.362	-0.417
	(0.402)	(0.625)	(0.600)	(0.550)	(0.303)
Education	-0.871**	-1.374***	-0.696	-0.818	-0.005
	(0.384)	(0.529)	(0.533)	(0.576)	(0.267)
Food availability at the end of month	0.846	2.232**	0.028	-0.015	-0.096
	(0.591)	(0.886)	(0.745)	(0.737)	(0.472)
Moderate physical activities (30 min) yesterday	0.551	0.553	0.692	1.686**	0.488
	(0.503)	(0.781)	(0.703)	(0.662)	(0.381)
Vegetables consumption yesterday	0.716*	0.551	0.885*	1.564***	-0.019
	(0.368)	(0.515)	(0.508)	(0.550)	(0.239)
Physical activities at home per week 2 or 3 times	-1.292**	-0.625	-1.666**	0.013	-1.379**
	(0.607)	(0.932)	(0.806)	(0.715)	(0.569)
4 or 5 times	-1.203*	-1.532*	-0.822	-0.539	-1.303**
	(0.653)	(0.924)	(0.891)	(0.804)	(0.611)
6 or more times	-1.584**	-2.031**	-1.037	-0.838	-2.195***
	(0.718)	(1.002)	(1.038)	(0.870)	(0.617)
Vegetables provision at home	-0.197	-0.420	0.005	-0.298	0.360
	(0.410)	(0.561)	(0.567)	(0.596)	(0.306)
Vegetable snack making demonstrations	1.039**	0.696	1.344**	1.484**	-0.239
	(0.410)	(0.674)	(0.539)	(0.612)	(0.299)
Days of parents child walking exercise last week	0.007	0.188	-0.124	0.129	0.110
	(0.106)	(0.163)	(0.138)	(0.155)	(0.084)
Encouragement from teachers	-1.912	-2.099	-2.140	-2.178	0.079
	(1.363)	(1.636)	(2.450)	(1.426)	(0.896)
% of Minority	-1.239	-2.026	-1.299	-3.186	-1.047
	(1.519)	(2.614)	(1.921)	(2.208)	(1.048)
% of Free lunch	1.726	3.352	0.152	2.366	-2.571*
	(2.021)	(2.862)	(2.971)	(3.145)	(1.432)
Time effect	0.175	-0.266	0.263	0.150	-0.417
	(0.454)	(0.643)	(0.648)	(0.563)	(0.351)
Observations	529	222	307	233	296
Adj.R-squared	0.952	0.958	0.948	0.970	0.981
F-statistics	641.079	369.802	354.078	449.974	1193.736
Under Identification Test (Kleibergen-Paap LM Statistic)	41.599	17.887	21.634	18.214	22.379
Weak identification Test (Cragg-Donald Wald F statistic)	77.396	33.310	35.587	36.011	36.917

*p<.1, ** p<.05, *** p<.01

were found among boys in the non-improvement group (β=1.176) and girls in the improvement group (β=1.472). These results indicate that for boys, the BMI values of those who were not making any improvements in BMI categorization from $t1$ to $t2$ were affected by interactions with their peers, i.e. the BMI value of a boy in the non-improvement group increased 1.176 points when his peers' BMI increased one point. On the other hand, for girls, the BMI values of those who were making improvements in BMI categorization from $t1$ to $t2$ were strongly affected by interactions with their peers, i.e. the BMI of a girl in the improvement group increased 1.472 points when her peers' BMI increased one point. No significant peer effects were found either in the improvement group for boys or the non-improvement group for girls.

2.5 Discussion

Our analysis focuses on the general peer effects and their differences by sex and BMI trend categorization groups. Evidence shows that intervention program results are different depending on the length of time duration; intervention results over shorter periods are typically more significant than longer periods (Nemet et al. 2005). However, students' BMI collection for TGEG program is at an interval of about six months and the rate of change in BMI from the previous six months prior to enrolling in TGEG is unknown. In addition, children at the age of 9 to 11 years would be influenced by the maturation effects and the natural growth accompanied by increasing BMI values for this age range as shown by the CDC 2000 Children's Growth

Table 2-5: Sex differences of peer effects across BMI categorization groups

	Non-Improvement Group & Male	Improvement Group & Male	Non-Improvement Group & Female	Improvement Group & Female
Peer effect	1.176**	0.213	0.420	1.472***
	(0.484)	(0.659)	(1.895)	(0.343)
Age	0.259	1.299	1.441	-0.918
	(0.980)	(1.172)	(3.085)	(0.631)
Marital	-0.674	-0.673	1.280	-0.592
	(0.787)	(0.620)	(1.611)	(0.363)
Education	-1.244*	-0.377	-0.666	0.258
	(0.718)	(0.458)	(0.813)	(0.349)
Food availability at the end of month	1.116	0.297	-0.548	0.199
	(1.060)	(0.931)	(1.114)	(0.568)
Moderate physical activities (30 min) yesterday	1.237	0.637	1.784*	0.941**
	(0.856)	(0.836)	(1.004)	(0.469)
Vegetables consumption yesterday	1.173	0.568	1.581*	-0.336
	(0.754)	(0.392)	(0.876)	(0.316)
Physical activities at home per week 2 or 3 times	-0.550	-1.568	-0.189	-1.617**
	(0.967)	(1.216)	(1.221)	(0.675)
4 or 5 times	-1.322	-1.787	-0.343	-1.421*
	(0.995)	(1.176)	(1.097)	(0.812)
6 or more times	-1.823*	-2.458**	0.144	-2.360***
	(1.043)	(1.052)	(1.297)	(0.805)
Vegetables provision at home	-0.121	0.516	0.122	0.247
	(0.668)	(0.475)	(1.058)	(0.364)
Vegetable snack making demonstrations	0.910	-0.789	1.669*	0.070
	(0.847)	(0.652)	(0.945)	(0.341)
Days of parents child walking exercise last week	0.120	0.241	0.078	0.019
	(0.198)	(0.176)	(0.213)	(0.083)
Encouragement from teachers	-1.319	2.836	-2.205	-0.458
	(1.373)	(2.520)	(6.953)	(1.125)
% of Minority	-5.178*	-0.264	-1.861	-0.777
	(3.033)	(2.933)	(3.028)	(1.144)
% of Free Lunch	2.550	-0.454	3.509	-4.755**
	(3.610)	(2.216)	(7.879)	(1.878)
Time effect	-1.155	-1.011	0.351	-0.124
	(0.771)	(0.784)	(0.999)	(0.457)
Observations	97	125	136	171
Adj.R-squared	0.975	0.976	0.965	0.983
F-statistics	305.993	641.769	275.129	672.449
Under Identification Test (Kleibergen-Paap LM Statistic)	15.802	5.072	4.342	17.429
Weak identification Test (Cragg-Donald Wald F statistic)	30.488	8.623	3.478	26.964

* p<.1, ** p<.05, *** p<.01

Chart (Kuczmarski RJ et al. 2002). It is possible that the rate of change in BMI was steeper prior to the study and participation in TGEG slowed this increase.

2.5.1 Peer Effects in Terms of Behavioral Explanations

Our results reemphasize the effectiveness of doing physical activities on students' BMI values and examine the distinctions between the effectiveness of different physical activities intensities among boys and girls. More specifically, higher physical activity intensities, over three times per week compared to none or little activity per week, are associated with a decrease in boys' BMI. Median physical activity intensities, two to three times per week compared to none or few activities per week, are associated with a decrease in girls' BMI. Previous studies find that during the age of 9-13, boys spend more time on moderate and vigorous physical activities on a daily basis compared to girls (Sherar et al. 2007). Furthermore, the calories consumed by boys doing moderate and vigorous activities are higher than girls (familydoctor.org 2015). In this regard, physical activities prove to lower students' BMI and keep or move students into a normal BMI categorization, which serves as group identification in this analysis.

Children's eating behavior is more controlled or influenced by parents in terms of generic and environmental factors (Scaglioni et al. 2011). Regarding generic factors, food preference of children is generally influenced by tastes and preference of their parents; regarding environmental factors, family's income level, parent life styles, and attitudes towards body image all might influence children's eating behavior (Scaglioni et al. 2011). Hence, compared to physical exercises, eating behavior is not likely to arouse the peer influence to the extent of physical exercises because parents have more control or influence on food preference and eating behavior. Moreover, considering the high percentage of children participating in the free lunch program in the sample, there is not much power among students to determine what to eat, although they do learn about healthy eating and gain nutrition knowledge in the classroom through the intervention.

2.5.2 Justification of Sex Difference in Peer Effects in Terms of Psychological Explanations for Social Group Categorization

The results of the peer effects across BMI trend categorization groups show that sex differences on peer effects are closely related to the BMI trend categorization status. Relatively speaking, boys are more likely to be influenced by their interactions with peer towards the direction of unhealthy BMI categorization; to the contrary, girls are more likely to be influenced by interaction with peer towards the direction of healthy BMI categorization. Girls in the improvement group benefit by their access to the group and their efforts to maintain membership in it.

Body weight, as an indicator of body image and activity participation, reflects how students evaluate themselves and determines with whom they would like to interact. Our analysis suggests that the social network, with the underlying categorization and separation, such as maintaining a presence in the improvement group or not, is associated with the different levels of peer effects. The BMI categorization determines the scope of the social network, and also influences the intensity of interactions among members in the network.

Sex differences are normally reviewed under a different relationship process, which includes behavioral and social-cognitive styles, stress and coping, and relationship provisions (Rose and Rudolph 2006). For example, “The Male Warrior Hypothesis”, that examines inter-group and out-of-group relations among boys, proposes strong preference for inter-group social hierarchy (McDonald et al. 2012). This inter-group identification shows close dependency on factors such as social attitudes across different cultural backgrounds. In contrast, boys are more likely to exhibit competition and violence towards out-of-group members to ease the potential psychological discomfort in case of intergroup conflict (McDonald et al. 2012). To explain the peer effect among boys in the non-improvement group, it is likely that they build their own network possibly holding the same or similar beliefs about exercising habits and body image. Moreover, improvements in terms of gradually doing more daily exercise by members outside of the group may be seen as a threat, with a risk of being ignored by boys.

Generally, girls are found to be more prone to arouse jealousy by their peer’s physical attractiveness (Buss et al. 2000). Moreover, girls associate body dissatisfaction with self-esteem but boys do not (Furnham et al. 2002). In contrast to boys, girls in the improvement group perceive body weight (which is closely related to body image) as a barrier for a higher level social network. Psychological experiments show that when girls see identification for belonging to a specific group which could improve their self-esteem, they adopt behavior to identify, obtain and keep group membership (Chen and Li 2009, Shih et al. 1999). This explains why girls in the improvement group might develop their social network and how other members in this group influence them.

2.6 Implications for Health Behavior or Policy

Our results suggest that understanding peer effects for students at this relatively young age adds critical information for policy makers and program planners seeking to improve classroom curriculum or target health intervention change. Both curricula and targeted messaging should be tailored to children that include positive peer role models, especially given the strong influence of peers at this age. Our study focused on individuals attending Title I schools (i.e. schools serving high proportion of students from low-income families) that may be particularly vulnerable. Future studies should continue to include individuals from low socioeconomic backgrounds given the well-known health disparities that exist in several health-related outcomes (Berkman et al. 2011, Krieger et al. 2003).

Traditional health education or intervention measures targeting elementary school students involve physical education and dietary education in multiple settings including the school, family, and community. However, the effectiveness of health education or intervention is rarely investigated from the psychological or social perspectives of students. Peer effects can be advantageous or disadvantageous to group members; therefore, the health-related classroom curriculum or interventions should be tailored with encouragement from key referents including, but not limited to, positive peer role models, highly respected community members, teachers, and parents. Furthermore, more interactions between teachers and students' parents also may hold promise with the goal of promoting the students' physical activities at home and involving parents in developing students' healthy lifestyle behaviors through positive influence.

The analysis of sex differences in peer effects is grounded in the difference between two BMI trend categorization groups. The improvement and non-improvement status regarding BMI serves as a threshold for the group identity, which helps explain the underlying social group categorization and according behavior in specific groups by sex. However, group identity could be based on other categorization methods and not limited to this one specific way. Future research questions should focus on longer time periods to investigate how peer effects on health-related outcomes change as children grow into adolescents and adolescents become adults. Both a better understanding of peer effects in a dynamic context and the associated sex differences may help researchers improve the design of certain health-related interactions and enable them to tailor targeted school health education.

Survey data collected in this study were from a limited number of public elementary schools located in four different counties in Texas. Additionally, these schools were characterized by a high percentage of students from low-income families. Consequently, the results might not be generalizable to students in other geographic locations within the US or from different socioeconomic backgrounds. Future research related to peer effects should be conducted on larger and more diverse samples to increase generalizability for a broader base. In summary, our findings surrounding the psychological and social influences of peer effects provide new perspectives that can be particularly helpful in identifying critical targets for effective health education, especially among vulnerable populations.

3 IMPACTS OF PLAYING AFTER SCHOOL ON ACADEMIC PERFORMANCE: A PROPENSITY SCORE MATCHING APPROACH

3.1 Introduction

After school activities usually involve but are not limited to taking part in physical activities, 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 activities is important for children and adolescents. It is particularly important for children aged eight to eleven as part of their regular physical activities for health purposes.

Participating in physical activities not only promotes a healthy and active lifestyle, but also fosters desired character traits of children (Dunn et al. 2003, Strong et al. 2005). Previous research assesses the effects of participation 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, Fauth et al. 2007, Simpkins et al. 2005). However, there exists an inconsistency as to whether doing physical activities improves academic performance and how much the improvement is if any (Taras 2005). Tomporowski et al. (2008) find that participating in physical activities is related to improved discipline and academic performance[1]. Yet a study conducted in Canada shows that physical activities have a weak negative relationship with academic performance (Tremblay et al. 2000).

[1] Other studies demonstrate positive associations between physical fitness and academic performance among third to fifth grade students in the United States (Castelli et al. 2007, Coe et al. 2006).

In this paper, we document the effects of playing on sports teams or clubs after school (hereinafter referred to as playing after school) on academic performance among fourth grade students relying on data from a large-scale survey in the United States. We highlight that in addition to intrinsic characteristics of students, the extent to which after school activities affect academic performance depends on extrinsic factors such as parental involvement and neighborhood environments (Fauth et al. 2007, Dunn et al. 2003). For instance, students with greater parental involvement and supervision might receive larger benefits from playing after school. In order to capture the heterogeneous effects of playing after school, we analyze the effect by separating the overall sample according to whether parents check their children's homework and set specific times for after school homework.

Our research accounts for two issues not addressed in the previous literature. First, most studies assessing the association between physical activities and academic achievements are built on intervention programs. External validity is questionable due to a limited number of participating students. Results from small scale intervention programs might not be generalizable to larger population. Another drawback regarding the methodology normally used in the literature lies in the fact that traditional ANOVA and OLS regressions do not take self-selection bias into account. For example, it is possible that students who participate in physical activities are energetic and intelligent thus perform better in academic studies as well. Comparatively, students who are physically inactive may tend to spend less time studying due to lack of enthusiasm or energy. In order to avoid this potential bias, we utilize a propensity score matching (PSM) approach (Rosenbaum and Rubin 1983). Propensity score is the predicted probability of students being in the treatment group of playing after school. The predicated score summarizes the dissimilarity between students in the control group and the treatment group. Conditional on the propensity score, students' participation in the treatment group is random. Thus, academic performance is comparable between students with similar propensity scores.

By means of propensity score matching, we show that playing after school significantly increases math and science test scores. This effect is stronger among students with high levels of parental involvement and supervision, but weaker or nonexistent among students with low levels of parental involvement and supervision.

The rest of the paper proceeds as follows. The next section outlines the empirical strategy. Section 3 describes the data. Section 4 conducts several diagnostics and presents the results. The results are discussed in Section 5. The last section concludes.

3.2 Methodology

3.2.1 Identification Strategy

The 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 cost or ethical issues.

The concept of PSM is to match participants being treated to non-treated participants in the control group with similar characteristics (Dehejia and Wahba 1999, Rubin 1974, Rosenbaum and Rubin 1983). Instead of using high dimensional matching functions of observed covariates, the propensity score is a simplified unidimensional probability and defined as ‘the probability of participating in a program given observed individual characteristics (Caliendo and Kopeinig 2008, Austin 2011, Rosenbaum and Rubin 1983). To be specific, the propensity score in this study is the probability of an individual student participating in playing after school conditional on observed characteristics of schools, teachers and their families. Thus differences between students in the treatment and the control group with the same or similar propensity scores are attributable to playing after school.

Covariates associated with treatment participation are included in the analysis. Table 3-1 documents the matching variables used in this study, including the characteristics of schools, teachers and family background of students. We also report the means and formal tests to show the difference between students who play after school and those who do not play after school. The results of *t*-tests indicate that students in the control group and the treatment group are significantly different in most characteristics. The last column of Table 3-1 shows the result of a logistic regression of treatment participation on the observed characteristics. Predictors of “playing after school” include a set of variables such as gender, race and family background of students, supervision from parents, and characteristics of schools and teachers.

3.2.2 Assumptions

To apply the PSM method, two standard assumptions are required to validate the identification strategy (Caliendo and Kopeinig 2008, Rosenbaum and Rubin 1983).

Assumption 1 is called unconfoundedness. This assumption re-emphasizes that conditional on the propensity score, the treatment participation of "playing after school" is random. Also, students with the same score are supposed to have the same distribution of characteristics of schools, family background and teachers.

Assumption 2 is known as Overlap. The overlap assumption is also known as common support, which is crucial in the context of non-parametric propensity score matching. This assumption ensures that students in the control group and the treatment group have substantial overlap in propensity scores to be compared. Conditional on characteristics of schools, teachers and family background of students, there must be a positive probability of finding a treated student and an untreated student to make sure that each treated student can be matched with an untreated student. If a treated student with certain combinations of characteristics cannot be matched by any untreated student in the comparison group, it is impossible to estimate the treatment effect.

3.2.3 Matching Algorithm

After obtaining the propensity score, we need to use it to match treated students with untreated students. To obtain robust results, we utilize different matching algorithms including nearest neighbor matching (NNM), caliper and radius matching (CRM) and kernel matching (KM) (Caliendo and Kopeinig 2008, Imbens 2014, Heckman et al. 1997, Heckman et al. 1998).

Through the NNM algorithm, the estimation process matches students who play after school with their counterparts who do not play after school with the closest propensity score. The CRM algorithm matches students who play after school with all counterparts who do not play after school within a predefined neighborhood of propensity score[2]. 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 who do not play after school 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 of the above mentioned algorithms are used in this study to check the robustness of the results. Moreover, a bootstrap process is applied in the PSM to obtain robust standard errors (Bai 2013).

3.3 Data

3.3.1 Survey

Our data comes from the Trends in International Mathematics and Science Study (TIMSS) 2011[3]. This study is conducted by the International Study Center, Lynch School of Education, Boston College, and the International Association for the Evaluation of Educational Achievement every four years (NationalCenterforEducationStatistics 2015).

TIMSS-US is conducted to obtain math and science assessments for fourth grade students. Students at participating schools take standardized math and science tests and

[2] The radius is set to 0.05 in this study.
[3] TIMSS 2011 is the latest survey available.

Table 3-1: Covariates- summary statistics and the Propensity Score.

	Means			PS Logit
	Treated	**Control**	**Difference**	**Coefficient**
Student age	10.218	10.207	0.011	0.006
Student gender: female	0.468	0.573	-0.105***	-0.374***
Race: Whites=1	0.559	0.403	0.156***	0.195**
Race: Blacks=1	0.114	0.120	-0.007	0.065
Race: Hispanics=1	0.222	0.336	-0.114***	-0.281***
Race: Asians=1	0.030	0.067	-0.037***	-0.902***
Race: Multiracial/Other=1	0.076	0.073	0.002	0.000
Have computer at home	0.948	0.913	0.035***	0.123
have own room at home	0.766	0.646	0.119***	0.418***
have videogame at home	0.960	0.934	0.027***	0.397***
have internet at home	0.884	0.811	0.073***	0.323***
Frequency of using computer: high	0.823	0.778	0.044***	0.088
Parents check homework	0.881	0.845	0.036***	0.324***
Percent of students of economic disadvantage	0.391	0.551	-0.160***	-0.416***
Type of school: public=1	0.976	0.984	-0.008***	-0.238
Students background composition: more affluent	0.189	0.126	0.064***	0.068
School location: low income area	0.349	0.465	-0.116***	-0.133
School location: medium income area	0.568	0.481	0.087***	-0.153
School location: high income area	0.083	0.054	0.029***	0.000
School emphasis on students' academic success	0.840	0.808	0.032***	0.049
School discipline: high	0.629	0.575	0.053***	-0.003
School help: parent deal with homework	0.635	0.661	-0.027***	-0.123**
School provide parents with supervising material	0.416	0.410	0.006	0.068
days in school per week	4.997	4.998	-0.001	-0.262
Total hours for school daily	6.037	6.056	-0.019	-0.049
Teacher gender: female	0.877	0.882	-0.005	-0.159**
Experience: less than five years	0.141	0.159	-0.017***	-0.136*
Experience: five to twenty years	0.614	0.601	0.013	0.015
Experience: more than twenty years	0.245	0.240	0.005	0.000

* p<0.1, ** p<0.05, *** p<0.01

complete questionnaires about their family resources, personal studying habits, and attitudes towards school. Meanwhile, surveys of schools and teachers are distributed to principals and teachers separately. Information is collected about teaching facilities, computer resources, and school-parent interactions. Demographic information of teachers and their work experience are included in the teacher's survey.

In total, there are 369 schools, 767 teachers and 15,061 students included in our analysis. Please refer to Table 3-2 for more details about the sample. The average age of students in this study is 10 years. Approximately 50.4% of participating students in TIMSS are female. Non-Hispanic Whites account for almost half of participating students. Non-Hispanic Blacks, Hispanics and Asians are about 11%, 26% and 4% respectively.

Approximately 40% of participating schools are characterized by a large percentage (more than 50%) of students from economically disadvantaged families. Nearly half of the schools are located in urban or suburban areas, and about 41% are located in medium sized cities or more remote rural areas. Over 85% of schools are public schools and about 2% are private schools or charter schools. On average, teachers have more than 27 years of teaching experience.

3.3.2 Treatment Variable and Grouping Variables

According to reports from the Department of Education and the US Census Bureau, physical activities after school mainly consist of "Sports Playing" and "Boys and Girls

Table 3-2: Summary of descriptive statistics.

Student	Observations		15,061
	Average Age		10
	Gender		
		Female	50.36%
	Race/Ethnicity		
		Non-Hispanic White	49.37%
		Non-Hispanic Black	11.39%
		Hispanic	25.70%
		Asian	4.24%
School	Observations		369
		Students from Economically Disadvantaged Homes	
		0 to 25%	29.11%
		26 to 50%	20.50%
		More than 50%	40.58%
		Population	
		More than 500,000 People	12.02%
		100,001 to 500,000 People	17.16%
		100,000 People or Fewer	59.84%
		Locality	
		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	
		High	6.49%
		Medium	47.89%
		Low	35.20%
		Type of School	
		Public	85.42%
		Private	1.46%
		Charter	0.94%
Teacher	Observations		767
	Gender		
		Female	74.41%
		Years of Teaching Experience	27

Club/ Scouts" (Bureau 2014, Education 2006). Therefore, the treatment dummy variable of "playing after school" is composed based on two questions on the survey of students: "*Do you play on a sports team outside of school*?" and "*Do you belong to a club outside of school (like Girl Scouts, 4-H, or Boys and Girls Club)?"*. We define "playing after school" as 1 if students answer "Yes" to either one of the two questions above; otherwise the treatment dummy is defined as 0.

To uncover potential heterogeneous effects of playing after school according to different levels of parental involvement, we have three grouping variables based on parents' behavior, including checking their children's homework, making sure that their children set aside time for homework, or doing both (hereinafter referred to full supervision). For example, we estimate the effect of playing after school for students with full supervision, and then compare it to the effect of playing after school for students without full supervision.

First grouping: Parents check their children's homework versus parents do not check their children's homework;

Second grouping: Parents ask their children to set aside time to do homework versus parents do not ask their children to set aside time to do homework;

Third grouping: Parents do both versus parents do not do both.

For simplicity, we only report the results by the subgroup of students getting the full supervision from parents (the third grouping method) in the next section. Results by the first and the second grouping methods are shown in the appendix Table A1 to Table A4.

3.4 Results

3.4.1 Test of the Assumptions

We conducted the balance test and *Overlap* assumption test to check the validity of the method before reporting the results[4].

Firstly, we try to check the balance in covariates between the control and the treatment group. The main purpose of this balance test is to make sure there is no significant difference between treated students and untreated students after matching by comparing the mean of covariates between the control group and the treatment group. Figure 3-1 graphically represents the balance test results. The variables on the Y axis are the matching variables. The vertical line in the graph denotes zero mean-difference in the matching variable. The visual representation indicates that there are no significant differences of variables between students in the control and the treatment groups after matching.

Secondly, we assess the *Overlap* assumption by showing the density of the propensity score in Figure 3-2. A visual inspection demonstrates a large overlap of the density of propensity scores between the treatment group and the control group. It also implies that for students with certain combinations of characteristics who play after school, we can find their counterparts to be matched with who do not play after school.

[4] Unconfoundedness assumption cannot be directly tested.

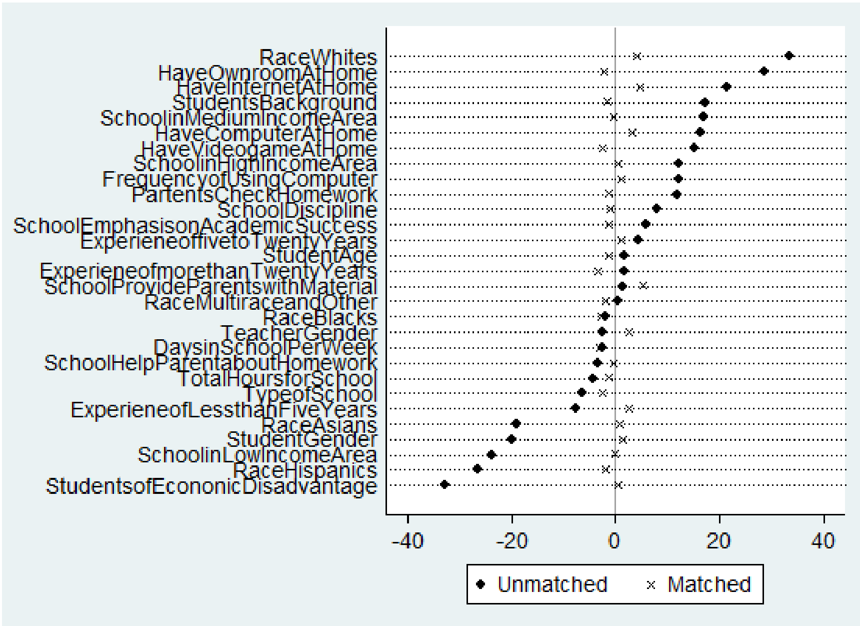

Figure 3-1: Balance check

Note: 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.

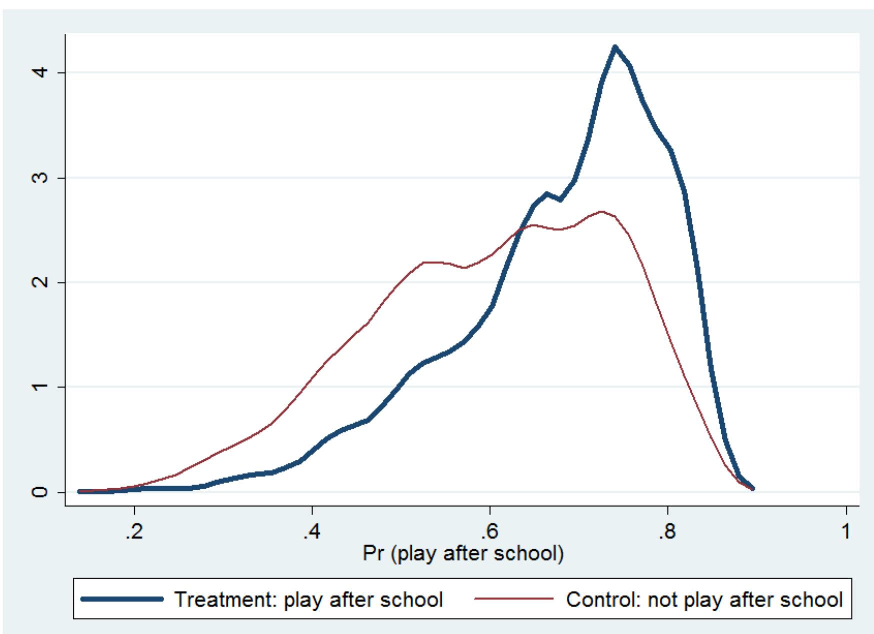

Figure 3-2: Overlap assumption test.

3.4.2 Estimated Effects

Average treatment effect (ATE) and average treatment on the treated (ATT) are commonly applied in program evaluations. Generally, ATE focuses on the treatment effect for the overall sample, and it represents the treatment effect of playing after school between students who play after school and students who do not play after school.

In contrast, ATT evaluates the treatment effects on the individuals being treated, and it represents the treatment effect of playing after school between students who play after school and the same students if they had not played after school. We care more about the treatment effect on test scores for students who play after school, thus ATT is preferred and estimated in this study.

We present ATT estimates of playing after school in Table 3-3. From left to right, each column shows the effect on math and science test scores estimated using the NNM, CRM and KM algorithm respectively[5]. Bootstrapped standard errors based on 200 iterations are provided in parenthesis below the estimates. For the overall sample, there are positive effects of playing after school on math and science test scores. The estimates of the effect on math scores range from 7.30 to 9.05 depending on different matching algorithms. In other words, students who play after school experience at least a 7.30-point increase in their math test scores. The estimates of the effect on science scores range from 3.39 to 5.66, which imply that students who play after school experience at least a 3.39-points increase in their science test scores.

[5] OLS estimates are not shown here and they are significantly different from the estimates from PSM, providing some evidence of selection bias.

Table 3-3: Treatment effects of playing after school for the overall sample

Matching Algorithm	NNM		CRM		KM	
General	Math	Science	Math	Science	Math	Science
ATT	9.053***	5.657***	7.317***	3.425***	7.297***	3.389**
	(1.850)	(2.019)	(1.485)	(1.290)	(1.439)	(1.469)
N	9937	9937	9937	9937	9937	9937
Females						
ATT	7.709***	5.056*	8.918***	5.335***	8.805***	5.249***
	(2.616)	(2.903)	(1.894)	(1.984)	(1.898)	(1.805)
N	5011	5011	5011	5011	5011	5011
Males						
ATT	3.562	-0.751	5.889***	1.691	5.780***	1.527
	(3.096)	(3.043)	(2.140)	(2.056)	(2.130)	(2.312)
N	4926	4926	4926	4926	4926	4926
Whites						
ATT	10.850***	6.525**	12.781***	8.243***	12.775***	8.241***
	(2.851)	(2.953)	(2.028)	(2.046)	(2.081)	(2.003)
N	5069	5069	5069	5069	5069	5069
Hispanics						
ATT	-1.954	-3.302	-4.222	-4.824*	-4.205*	-4.969*
	(3.597)	(3.807)	(2.746)	(2.733)	(2.485)	(2.981)
N	2538	2538	2538	2538	2538	2538
Blacks						
ATT	-5.645	-7.899	-1.923	-4.902	-1.999	-5.097
	(6.309)	(6.483)	(4.465)	(4.777)	(4.569)	(4.594)
N	1062	1062	1062	1062	1062	1062
Asians						
ATT	-1.808	-2.679	-1.387	-2.393	-1.727	-2.677
	(9.934)	(9.719)	(6.495)	(6.473)	(6.251)	(6.503)
N	482	482	482	482	482	482

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

We find a significant gender difference in the effect of playing after school. There is a strong positive effect on math and science test scores among female students using all the algorithms, but no significant effect on science test scores is found among male students. There is a positive effect on math test scores with the CRM and KM algorithm among male students. Similar to the results for the overall sample, the effect of playing after school is larger on math test scores (ranging from 7.71 to 8.92) than on science test scores (ranging from 5.06 to 5.34) among female students.

Regarding racial and ethnic heterogeneity, large positive effects on both math and science test scores are found among Whites. The estimates of the effect on math test scores range from 10.85 to 12.78 while the estimates of the effect on science test scores range from 6.53 to 8.24. There is no significant effect of playing after school on math or science test scores among Asians or Blacks. For Hispanics, there are weakly negative effects on math test scores with the CRM algorithm and on science test scores with the CRM and KM algorithm, both of which are significant at the 10% level.

Table 3-4 reports the ATT estimates of playing after school on academic test scores by restricting the sample to students with high levels of parental involvement and supervision. In general, positive effects of playing after school detected previously are accentuated in this case. It suggests that students with high levels of parental involvement and supervision, who also play after school have higher academic scores in both math (from 6.89 to 8.84 points) and science (from 5.79 to 5.88 points) test scores than if they had not played after school. There are significant positive effects on math and science test scores among female students and male students, with an exception of a nonsignificant effect on science score for male students using the KM algorithm. The

Table 3-4: Treatment effects of playing after school for students under full supervision.

Matching Algorithm	NNM		CRM		KM	
General	Math	Science	Math	Science	Math	Science
ATT	6.891***	5.876**	8.841***	5.872***	8.736***	5.788***
	(2.181)	(2.563)	(1.859)	(1.751)	(1.785)	(1.789)
N	6527	6527	6527	6527	6527	6527
Females						
ATT	8.704**	8.228**	9.918***	6.931***	9.854***	6.876***
	(3.174)	(3.507)	(2.471)	(2.443)	(2.382)	(2.475)
N	3439	3439	3439	3439	3439	3439
Males						
ATT	8.134**	6.990*	7.172**	4.195*	6.913***	3.845
	(4.040)	(3.755)	(2.911)	(2.829)	(2.952)	(2.631)
N	3088	3088	3088	3088	3088	3088
Whites						
ATT	12.579***	10.232***	15.559***	11.824***	15.541***	11.760***
	(3.439)	(3.536)	(2.555)	(2.290)	(2.409)	(2.258)
N	3382	3382	3382	3382	3382	3382
Hispanics						
ATT	-8.442	-6.345	-5.522*	-5.325	-5.537	-5.383
	(5.362)	(4.914)	(3.223)	(3.939)	(3.443)	(3.620)
N	1610	1610	1610	1610	1610	1610
Blacks						
ATT	-1.628	1.288	1.524	0.381	1.650	0.637
	(8.336)	(8.267)	(5.619)	(5.613)	(5.104)	(5.727)
N	698	698	698	698	698	698
Asians						
ATT	5.147	6.724	0.900	6.287	2.811	7.299
	(12.748)	(12.992)	(9.652)	(10.608)	(8.417)	(10.126)
N	284	284	284	284	284	284

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

magnitudes of the positive effects on math test scores (ranging from 8.70 to 9.92) and science test scores (ranging from 6.88 to 8.23) among female students are larger than the effects on math test scores (ranging from 6.91 to8.13) and science test scores (ranging from 4.20 to 6.99) among male students.

We again explore racial and ethnic heterogeneity. Positive effects are found on both math test scores (ranging from 12.58 to 15.56) and science test scores (ranging from 10.23 to 11.82) among Whites using three algorithms. In contrast, for Hispanics, a weakly negative effect is found on math test scores using the CRM algorithm. But we still do not find any significant effects of playing after school on math or science test scores among Blacks or Asians.

Table 3-5 documents ATT estimates of playing after school on academic test scores by restricting the sample to students with low levels of parental involvement and supervision. Generally, the positive effects of playing after school almost disappear. In general, a positive effect (ranging from 4.54 to 8.06) is found on math test scores using the NNM and CRM algorithms. We do not find any significant effect of playing after school among male students, and there is a positive effect on math test scores among female students with the CRM and KM algorithms. However, the magnitude of this effect are smaller than among female students receiving high levels of parental involvement and supervision shown in Table 3-4. A weak effect is found on math score (approximately 7.1) among Whites at the significance level of 10% using the CRM and KM algorithms. Similar to the effect among female students, the effect of playing after school is smaller than it is among Whites with high levels of parental involvement and

Table 3-5: Treatment effects of playing after school for students under no full supervision.

Matching Algorithm	NNM		CRM		KM	
General	Math	Science	Math	Science	Math	Science
ATT	8.063**	3.491	4.536**	-1.359	4.435	-1.479
	(3.737)	(3.780)	(2.451)	(2.691)	(2.746)	(2.524)
N	3410	3410	3410	3410	3410	3410
Females						
ATT	6.730	5.251	7.539**	2.756	7.414**	2.608
	(5.163)	(5.348)	(3.233)	(3.413)	(3.318)	(3.725)
N	1572	1572	1572	1572	1572	1572
Males						
ATT	1.199	-2.213	3.605	-2.955	3.521	-3.034
	(4.657)	(5.360)	(3.711)	(3.848)	(3.384)	(3.637)
N	1838	1838	1838	1838	1838	1838
Whites						
ATT	5.808	0.949	7.098*	0.689	7.126*	0.735
	(4.923)	(4.914)	(3.702)	(3.695)	(3.698)	(3.710)
N	1687	1687	1687	1687	1687	1687
Hispanics						
ATT	6.307	-0.895	1.223	-2.605	1.423	-2.512
	(6.847)	(7.042)	(4.112)	(4.794)	(4.521)	(4.324)
N	920	920	920	920	920	920
Blacks						
ATT	-8.916	-6.952	-9.333	-10.118	-9.775	-10.454
	(11.799)	(11.681)	(8.893)	(9.576)	(9.682)	(9.603)
N	361	361	361	361	361	361
Asians						
ATT	17.091	9.829	15.442	4.283	16.732	5.764
	(18.516)	(17.298)	(13.455)	(12.923)	(14.020)	(13.328)
N	195	195	195	195	195	195

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses. *p<0.1, ** p<0.05, *** p<0.01

supervision. There is no clear evidence of effects of playing after school on math or science test scores among Hispanics, Blacks or Asians if they do not receive full parental supervision.

3.5 Discussion

3.5.1 Heterogeneity in Effects of Playing after School by Parental Involvement

The estimates from the overall sample indicate that playing after school significantly increases math and science test scores of fourth grade students. Additionally, we use parental supervision as an indicator of involvement in academic studies of their children. Further analysis using the subgroup of students receiving full parental supervision and students not receiving full supervision allows us to see whether or not the effect of playing after school on academic performance varies with different levels of parental involvement. High (low) level of parental involvement and supervision is associated with significantly (weak or no) positive effects of playing after school on academic performance of their children.

A huge body of literature proves that greater parental involvement is linked to better academic performance of their children (Hara and Burke 1998, Jacobs and Harvey 2005). Dunn et al. (2003) find that parents from middle class families encourage and support their children to participate in various after school activities, and expect to instill self-esteem, responsibility and social skills into their children through after school activities. Our results are consistent with previous literature in this aspect.

Our findings also indicate that parental involvement not only affects the academic performance of their children in a direct and unidimensional way; parental involvement also influences the effect of physical activities on academic performance of their children. Moreover, engagement levels of students are different with various after school activities (Shernoff and Vandell 2007). Practically, high levels of parental involvement transfer into an enhancement of the engagement, motivation, self-regulation and self-efficacy of their children (Fan and Williams 2010, Gonzalez-DeHass et al. 2005). Thus, increased engagement level and self- efficacy encourage students to perform better not only in academic studies but also in other activities, and in turn boost the benefits from participating in other activities.

3.5.2 Heterogeneity in Effects of Playing after School by Gender

Our results also document significantly different effects by gender. Generally, female students benefit more from playing after school than male students.

Previous research identifies positive correlations between physical activities and self-esteem among twelve years old elementary school students (Tremblay et al. 2000). Furthermore, self-esteem of students is closely related with their self-evaluation, self-perceptions and academic performance. Pomerantz et al. (2002) indicate a large difference in the self-perceptions of competence, anxiety and depression between female and male students. Hence we believe there is a mechanism working through playing after school. Through this mechanism, female students increase their level of self-perception more, and in turn the increasing self-perception improves their academic performance.

3.5.3 Heterogeneity in Effects of Playing after School by Race

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

Evidence shows that differences in parental involvement on their children's academic performance is linked to differences in their socioeconomic status (Sui-Chu and Willms 1996). The underlying explanation for the heterogeneous effects might be rooted in socioeconomic status and cultural factors, such as expectations of educational success and parents' educational attainment, which vary among racial and ethnic groups (Blair et al. 1999, Huntsinger and Jose 2009). For example, maternal education partly answers the variation in parental involvement among racial and ethnic groups (Suizzo and Stapleton 2007). More specifically, Lee and Bowen (2006) find that European American parents and parents with higher education are more likely to be involved in educational activities with their children than Hispanic, African American parents and parents with lower educational levels. Comparatively, the cases with low level of parental support or guidance, and low education degree of parents occur more often in low income families, a majority of which consist of Hispanics and Blacks.

3.6 Conclusion

This paper uses a propensity score matching approach to estimating the treatment effect of playing after school on math and science test scores. Our results indicate that playing after school increases math and science test scores for fourth grade students, and this positive effect is stronger if students receive greater parental involvement, but weaker or nonexistent if students receive less parental involvement. These general findings shed light on future intervention programs design in terms of allocating the intervention components and incorporating parental involvement as a key factor. The findings are also instructive for schools to offer guidance to parents regarding how to better supervise and be involved in after school activities of their children. Furthermore, special attention should be given to Hispanic and Black students due to their vulnerability in terms of socioeconomic status. Parents of low income families should devote more time and involvement to both academic studies and after school activities for their children.

4 DOES MEDICAID ENHANCE EDUCATIONAL ACHIEVEMENT? EVIDENCE FROM A NATURAL EXPERIMENT

4.1 Introduction

Medicaid is a nationwide social health care program specifically designed for low-income individuals in the United States. Before the mid-1980s, Medicaid was initially targeted to pregnant women, children and disabled individuals from low-income families.[6] Starting in the mid-1980s, Medicaid experienced several expansions to include individuals who were previously not eligible due to age and family income restrictions (Holahan and Zedlewski 1991, Card and Shore-Sheppard 2004, Bitler and Zavodny 2014). Approximately 69 million people were enrolled in Medicaid in 2015. Medicaid and the Children's Health Insurance Program (CHIP) currently offer health coverage to over 31 million children; half of the low-income children in the United States are included in Medicaid, CHIP or both.[7] The total federal and state's financial spending on Medicaid reached $476 billion in 2014 (Kaiser Family Foundation 2016).

A substantial literature documents the positive effects of Medicaid expansion on health care utilization (e.g., hospitalization, emergency room visits) and health outcomes (e.g., lower obesity and mortality) (Currie and Gruber 1996, Currie et al. 2008, Finkelstein et al. 2011, De La Mata 2012, Meyer and Wherry 2012, DeLeire et al. 2013,

[6] Before the mid-1980s, Medicaid eligibility was closely linked to the program "Aid to Families with Dependent Children" (AFDC).
[7] See the detailed statistics at https://www.medicaid.gov/medicaid-chip-program-information/by-population/by-population.html.

Cardella and Depew 2014, Taubman et al. 2014, Boudreaux et al. 2015, Wherry et al. 2015).[8]

Empirical evidence shows a positive impact of prenatal or pregnancy care on early childhood health and cognitive development (Almond and Currie 2011, Currie and Almond 2011, Figlio et al. 2013). As a result, one may expect that Medicaid enrollment will considerably promote success in education achievement and in the labor market. However, in his influential work, Murray (1984) proposed a widespread argument that the short-term benefits provided by welfare programs harm the recipients by crowding out their work ethic and eroding their human capital in the long term. The long-standing debate over whether welfare programs are beneficial for recipients reflects broad interests from policy makers and researchers. However, to date, there has been thus far little work estimating the potential long-term effects of Medicaid on educational attainment.[9]

Our study fills this gap in the literature by examining the long-term impacts of Medicaid on high school and college completion through a regression discontinuity (RD) design, which takes advantage of the Omnibus Budget Reconciliation Act 1990 (hereafter, OBRA 1990) as a *natural experiment*. The eligibility expansion due to OBRA 1990 regulates that children born after October 1983 from families below the federal poverty line are eligible for Medicaid, while the cohorts born before October 1983 under

[8] See Bitler and Zavodny (2014) for a more comprehensive overview of studies about the impacts of Medicaid on health outcomes.

[9] Some empirical studies have investigated the impacts of disability insurance programs on human capital and labor force participation, including (Chen and Van der Klaauw (2008), Von Wachter et al. 2011), Maestas et al. (2013), Autor et al. (2015), French and Song (2014). Most of them provide some evidence that participation in disability insurance programs reduced employment.

the same conditions experienced considerably lower rates of Medicaid eligibility.[10] Therefore, individuals born immediately before October 1983 are ideal counterfactuals of individuals born immediately after October 1983, since they are non-eligible, but otherwise face the same environment. This discontinuous change in the likelihood of Medicaid enrollment created a plausible source of random variation that enables us to estimate the specific causal effect of Medicaid expansion on educational attainments using a RD design. The assignment of Medicaid enrollment is locally random around the threshold of October 1983, since parents were unable to expect the policy change in advance and manipulate the birth month of their children to gain Medicaid eligibility after 1990.

Taken together, the Medicaid expansion of 1990 is a useful *natural experiment* for studying the effects of health insurance programs for two major reasons. First, Medicaid covers a broader population than most other welfare programs. Second, OBRA 1990 provides a convincing exogenous variation to overcome the endogeneity of Medicaid enrollment and cleanly estimate the treatment effects of Medicaid.

Our results shed new light on the long-term causal effect of the Medicaid program on educational achievement in adulthood. We find that the OBRA 1990 Medicaid expansion is associated with adverse impacts on high school completion for the overall sample and subsamples of males and females. We also find heterogeneous effects by race/ethnicity. While Medicaid enrollment reduced high school completion rates for

[10] Due to the expansion, the eligibility rate for children in families whose income was below the poverty line increased from around 7% to 100%, which indicated a sharp discontinuity (Card and Shore-Sheppard 2004).

whites and Hispanics, blacks and Asians do not respond to the Medicaid expansion by decreasing high school completion. With respect to college completion, only Hispanics were negatively affected by Medicaid enrollment.

The rest of the paper proceeds as follows. The next section outlines our empirical strategy. Section 3 describes the data. Section 4 presents the results, while Section 5 conducts several diagnostics to validate our research design. We further discuss the underlying mechanisms for the results in Section 6. The last section concludes.

4.2 Empirical Strategy

Our goal is to identify the discontinuous change in educational attainments across the eligibility threshold of the birth quarter (October 1983). Assuming that other factors except eligibility are smooth across the threshold, this discontinuous change should reflect the causal effect of Medicaid. However, in this study, there is no tracking information of Medicaid enrollment in the 1990s. In this regard, an indicator variable of whether the birth quarter is after October 1983 is used as an instrument for Medicaid enrollment. Hence we estimate the "intent-to-treat" effect from the reduced-form RD design.

To perform the RD design, we follow Lee and Lemieux (2010) and employ both parametric models (second order global polynomial regressions) and nonparametric models (local linear regressions). To be specific, the first model is a second order global polynomial regression that allows flexible controls for quadratic trends on both sides of the threshold:

$$Y = \beta_0 + \beta_1 * I(X \geq 0) + \beta_2 * X + \beta_3 * X^2 + \beta_4 * I * X + \beta_5 * I * X^2 + \varepsilon \quad (1)$$

where Y is the outcome variable, such as whether an individual has completed high school, or whether an individual has earned a college degree. I is the discontinuity indicator of whether an individual was born after October 1983. It takes the value 0 if an individual was born before October 1983, and 1 otherwise. X is the running variable, i.e., the distance of an individual's birth quarter to the cutoff quarter (October 1983). For example, X equals 1 for an individual born in the first quarter of 1984, while X of an individual born in the third quarter of 1983 is -1. The RD estimator is given by the parameter β_1 that captures the unbiased estimate of the outcome gap between the control and the treatment group. The above model is in a sparse form and does not include any covariates. Covariates including age, gender, marital status and race/ethnicity are included in other specifications to test whether the estimates are sensitive to other factors. Since the discontinuous change in Medicaid eligibility does not depend on those demographic characteristics, the estimates should be similar with or without adding these covariates in the regressions. Window selection is associated with a trade-off between estimates bias and variance. We pre-defined a window width of 24 birth quarters on either side of the eligibility threshold (October 1983), thus cohorts born 6 years before and after October 1983 are included in the interval [-24, 23]. Models with a window of 16 birth quarters are also estimated as a robustness check.

The second model specification is a nonparametric local linear regression model:

$$Y = \beta_0 + \beta_1 * I(X \geq 0) + \beta_2 * X + \beta_3 * I * X + \varepsilon \quad (2)$$

This approach estimates the above linear regression using triangle kernel weights, which places higher weight to the observations closer to the cutoff point. Bandwidth selection is one of the critical problems in nonparametric analysis. With a wider bandwidth, variance is expected to be smaller at the expense of lower confidence in unbiasedness of estimates, and vice versa (Imbens and Lemieux 2008, Lee and Lemieux 2010). To determine the kernel bandwidth, we exploit two cross-validation methods, namely Imbens and Kalyanaraman (IK) bandwidth selector (Imbens and Kalyanaraman 2012) and Calonico, Cattaneo and Titiunik (CCT) bandwidth selector (Calonico et al. 2014).

Since Medicaid is particularly relevant for low-income families, both parametric and nonparametric models are estimated with the restriction of family income below 100% of the federal poverty line. The results still hold using the sample with family incomes below 150% of the federal poverty line.[11]

4.3 Data

The data used in this study are from the American Community Survey (ACS) 2014. The benefit of using the ACS data lies in its large representative sample nationwide, which provides sufficient observations to both sides of the threshold. The survey questions contain comprehensive information including demographics, education, employment status and family characteristics at the individual level.

[11] This part of the results is not shown in the paper but is available upon request.

Table 4-1: Summary of sample characteristics

	Overall	Under 100% Poverty line	Under 100% Poverty Line within 6-year Window
Sample Size	2,760,989	382,612	59,542
Average Age	38	31	31
Gender			
Female	54.30%	57.10%	61.36%
Race/Ethnicity			
Whites	75.80%	62.70%	62.70%
Blacks	10.70%	19.40%	18.52%
Hispanics	14.95%	24.49%	25.60%
Asians	5.49%	4.59%	4.98%
Marital Status			
Single	59.43%	83.03%	71.22%
Married	40.57%	16.97%	28.78%
Education			
High school or below	51.13%	68.33%	49.41%
College or Above	22.25%	7.81%	13.67%

There are a total of 2,760,989 respondents in the ACS 2014 data. The average age is 38 years old.[12] Females account for approximately 54.30% of all respondents. Approximately 75.80% of respondents are white. Hispanics, blacks, and Asian account for 14.95%, 10.70%, and 5.49% respectively. Please refer to Table 4-1 for more details about the sample.

We further summarized the sample characteristics for those who live under 100% of the federal poverty line and those who lived under 100% of the federal poverty line within a six-year window (this is the final sample we used for the estimation). The final sample consists of 59,542 respondents. The average age of the final sample is 31 years

[12] Considering the population who benefited from the Medicaid expansion in 1990, we exclude respondents who are veterans or have disabilities from the sample.

old. The percentage of whites (62.70%) and Asians (4.98%) are lower than those in the overall sample, meanwhile the percentage of Hispanics (25.60%) and blacks (18.52%) are higher than those in the overall sample. The percentage of individuals with a college or higher degree (13.67%) is lower than that of the overall sample.

Estimates from the RD design using 2014 data represent the treatment effect for individuals at the age of 31, who were born around the fourth quarter of 1983. Most individuals born around the threshold should have already graduated from college by 2014. Otherwise, if some individuals around the threshold are still studying in high school or college, the estimates of the effects of Medicaid on educational attainments may be misleading. Due to increasing tuition fees and some other reasons, the current average age for finishing college is around 30 years old (Bound et al. 2012). Hence, people in our dataset who are 31 years old are supposed to have finished high school and college even if they went back to school after working for a period of time.

4.4 Results

4.4.1 Estimates of the Effect of Medicaid Enrollment on High School Completion

Figure 4-1 is the graphic representation of high school completion rate by birth quarter distance to the cutoff point for the overall sample. The x-axis represents the running variable in the RD design, i.e., the distance of birth quarter to the cutoff quarter (October of 1983), and the vertical line denotes the cutoff quarter. The y-axis represents the high school completion rate. The dots shown on the graph are binned sample means;

the dots on the right hand side of the cutoff point indicate the treatment group while those on the left hand side indicate the control group. The solid lines are fitted values from the regression of high school completion on a second order polynomial in the birth quarter distance to the cutoff point (separately for observations on either side of the threshold). The visual representation of the graph reveals a sharp drop of high school

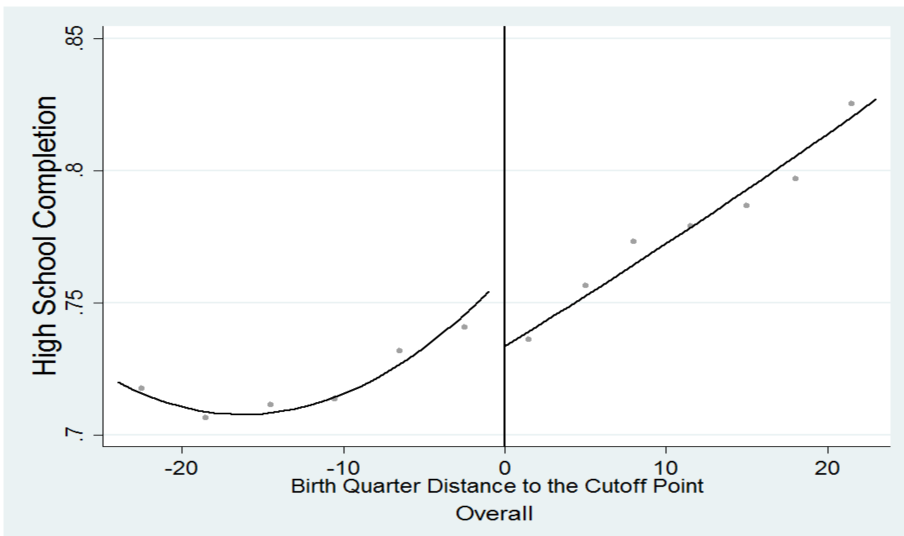

Figure 4-1: Effect of Medicaid enrollment on high school completion

completion rate across the eligibility threshold of October 1983 in general. Thus, respondents who enrolled in Medicaid are much more likely not to finish high school. Figure 4-2 illustrates the profile of high school completion by birth quarter cohorts for males and females separately, which both display downward shifts of high school completion rate across the threshold. Figure 4-3 shows high school completion rate by birth quarter distance to the cutoff point by splitting the sample into four racial/ethnic groups. A discernible gap of high school completion is evident around the threshold for whites and Hispanics. There is no evidence of such significant shifts for blacks. Although Asians experienced a jump in high school completion passing the eligibility threshold, the estimate is insignificant as shown in Table 4-2.

To investigate the effects in more detail, Table 4-2 reports the estimates of treatment effects of Medicaid enrollment on high school completion using the local linear regressions with IK bandwidth selector and CCT bandwidth selector (columns 1 and 2) and second order global polynomial regressions (columns 3-6). The results in columns 3 to 4 show the effect from the sparse form model without covariates, and the results in columns 5 and 6 show the estimates of the effect with covariates included. Different rows show the effects of Medicaid on high school completion based on the overall sample, by gender and by racial/ethnic groups respectively.

For the overall sample, results from the local linear regressions suggest that Medicaid enrollment decreases high school completion by 3.6 percentage points using the IK bandwidth selector and 3.9 percentage points using the CCT bandwidth selector. Results from the second order global polynomial regressions indicate that Medicaid enrollment decreases high school completion by 2.7 percentage points using a 6-year window and 4.0 percentage points using a 4-year window respectively without covariates. After controlling for age, gender, marital status and race/ethnicity, the negative effects decrease slightly to 2.5 percentage points using a 6-year window and 3.9 percentage points using a 4-year window respectively. Together, the results are robust

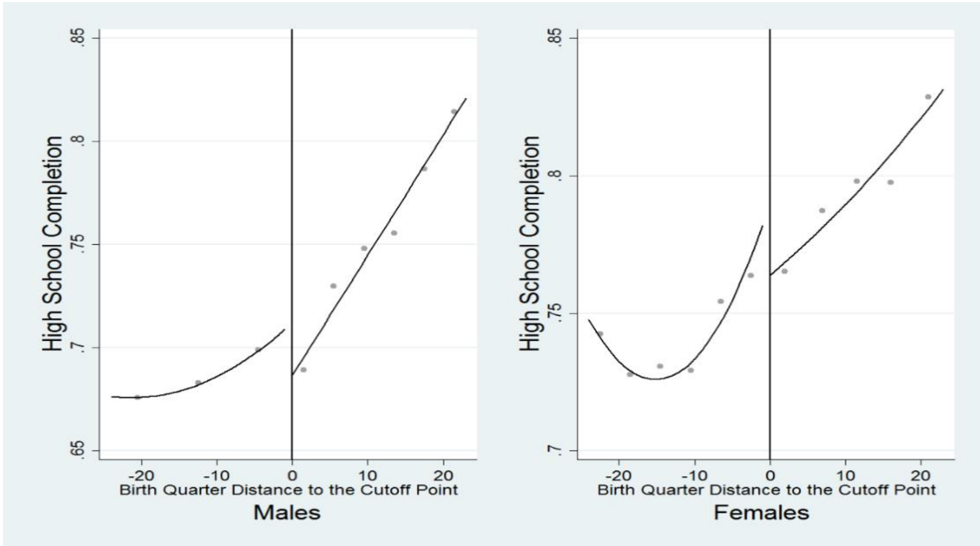

Figure 4-2: Effect of Medicaid enrollment on high school completion by gender

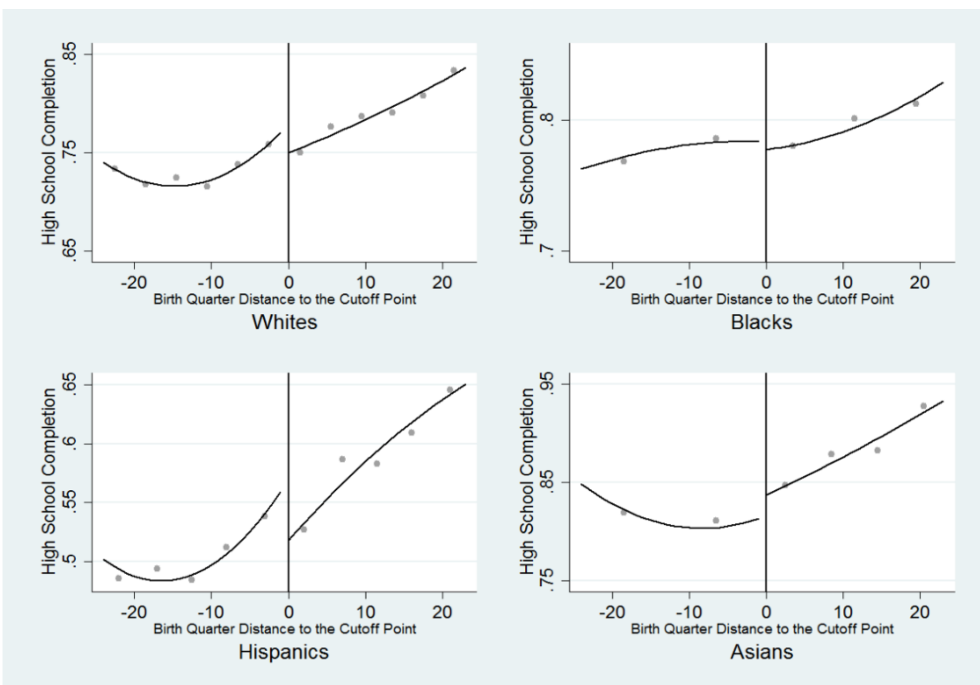

Figure 4-3: Effect of Medicaid enrollment on high school completion by racial/ethnic groups

Table 4-2: RD estimation results (High School Completion)

	Local Linear Regression		Second Order Global Polynomial Regression			
	(1)	(2)	(3)	(4)	(5)	(6)
	IK Bandwidth Selector	CCT Bandwidth Selector	6-Year Window (without covariates)	4-Year Window (without covariates)	6-Year Window (with covariates)	4-Year Window (with covariates)
Overall	-0.036***	-0.039***	-0.027**	-0.040***	-0.025**	-0.039***
	(0.012)	(0.013)	(0.011)	(0.014)	(0.011)	(0.013)
N	25728	20789	59542	39270	59542	39270
Males	-0.049**	-0.049**	-0.026	-0.048**	-0.021	-0.045**
	(0.023)	(0.023)	(0.018)	(0.023)	(0.018)	(0.022)
Sample Size	7991	7991	23007	14978	23007	14978
Females	-0.023*	-0.028*	-0.026**	-0.033**	-0.027**	-0.035**
	(0.012)	(0.015)	(0.013)	(0.017)	(0.013)	(0.016)
N	21969	14364	36535	24292	36535	24292
Whites	-0.047***	-0.047***	-0.028**	-0.054***	-0.030**	-0.055***
	(0.018)	(0.017)	(0.013)	(0.017)	(0.013)	(0.017)
N	11635	11635	37333	24637	37333	24637
Hispanics	-0.058**	-0.058**	-0.051**	-0.073**	-0.043*	-0.065**
	(0.028)	(0.028)	(0.024)	(0.030)	(0.024)	(0.030)
N	6148	6148	15242	10247	15242	10247
Blacks	-0.009	-0.022	-0.006	-0.003	-0.006	-0.003
	(0.022)	(0.028)	(0.024)	(0.030)	(0.024)	(0.030)
N	6607	4323	11027	7355	11027	7355
Asians	0.027	0.013	0.021	0.023	0.025	0.025
	(0.036)	(0.051)	(0.041)	(0.054)	(0.041)	(0.054)
N	2342	1184	2969	1828	2969	1828

Notes: Standard errors are reported in parentheses.
* *p*<0.1, ** *p*<0.05, *** *p*<0.01

to different window widths and the inclusion of covariates.

Negative effects are also found among subsamples of males and females with an exception of no significant effect for males using the second order global polynomial regression with a 6-year window (shown in column 3 and 5). Estimates from local linear regression implies that Medicaid enrollment decreases the high school completion by 4.9

percentage points for males and 2.3 ~2.8 percentage points for females. We find no clear evidence of gender difference in the estimates.

Whites and Hispanics account for a great share of the treatment effect under all model specifications, while no significant effect is found among either blacks or Asian. Notably, the negative effect is larger among Hispanics than among whites under all specifications. More specifically, the negative effects of Medicaid enrollment on high school completion range from 4.3 to 7.3 percentage points among Hispanics and 2.8 to 5.5 percentage points among whites considering all specifications.

4.4.2 Estimates of the Effect of Medicaid Enrollment on College Completion

We find little evidence of the impact of Medicaid enrollment on college completion. Figure 4-4 does not reveal discernible shift of college completion rate by birth quarter across the threshold for overall sample. Similarly, no noticeable discontinuous changes are found in the fitted lines across the threshold for males and females in Figure 4-5. Figure 4-6 displays the smoothness of the fitted line except the downward shift of fitted line for Hispanics in the lower-left corner. In general, the graphic representations suggest little effect of Medicaid on college completion.

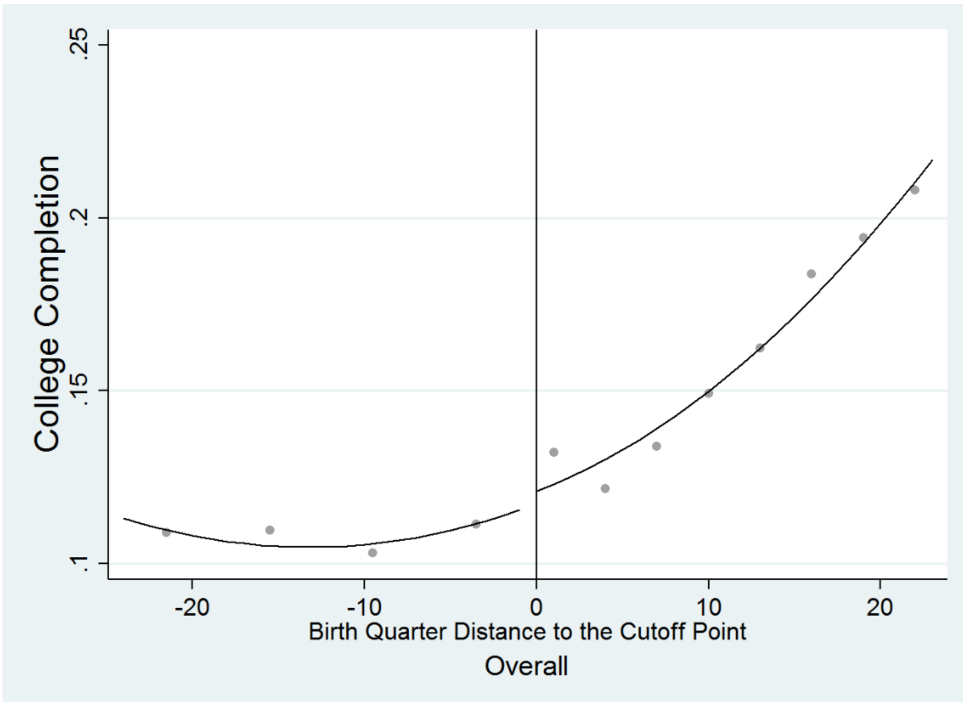

Figure 4-4: Effect of Medicaid enrollment on college completion

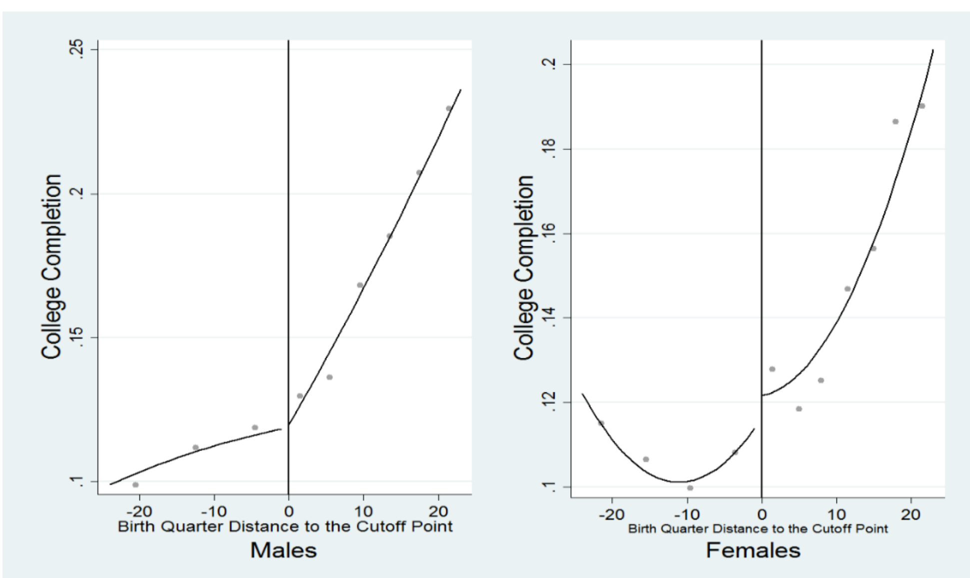

Figure 4-5: Effect of Medicaid enrollment on college completion by gender

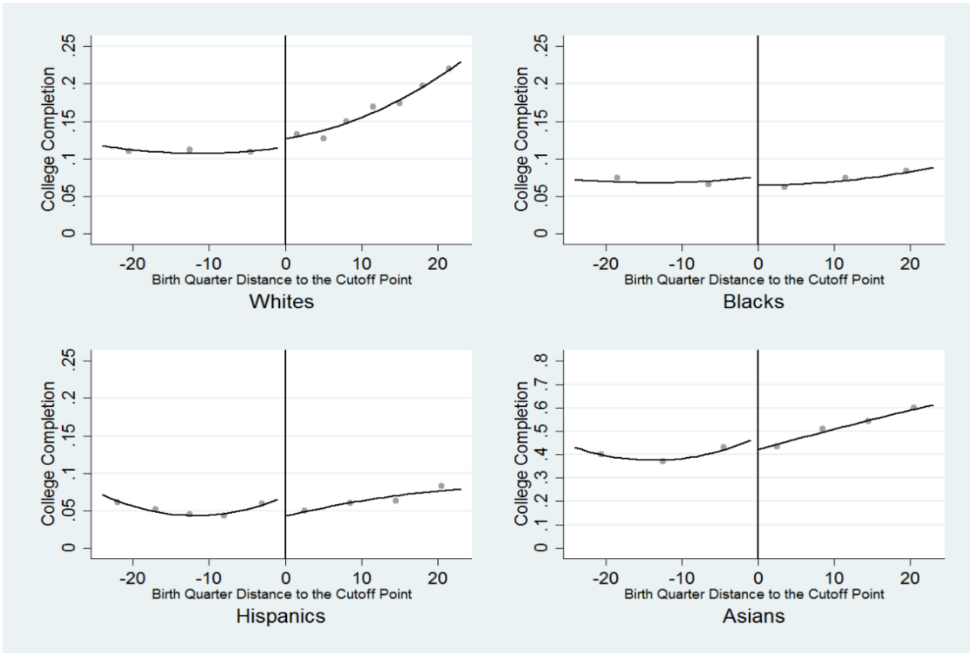

Figure 4-6: Effect of Medicaid enrollment on college completion by racial/ethnic groups

Table 4-3 reports the estimates of treatment effects of Medicaid enrollment on college completion. Accordingly, there are no significant effects estimated from either local linear model or second order global polynomial model based on the overall sample, or any subsamples except for Hispanics. The general result indicates that Medicaid enrollment does not affect college completion with an exception for Hispanics. Medicaid enrollment decreases college completion by 2.7 percentage points for Hispanics using nonparametric local linear model with the IK bandwidth selector. The estimates from second order global polynomial models imply that the decreasing effects range from 2.6 ~ 3.6 percentage points.

Taken together, we find heterogeneous effects by race/ethnicity, which await further investigation of the underlying mechanism. In particular, Medicaid enrollment does not affect blacks or Asians but affects Hispanics and whites in high school completion, while Hispanics are also adversely affected by Medicaid on college completion.

4.5 Validating the Research Design

The validity of our empirical strategy relies on the local randomization around the birth quarter eligibility threshold. Following Lee and Lemieux (2010), we examine the validity of the RD design using three diagnostics tests.

4.5.1 Manipulation

One concern with RD design is the manipulation of the running variable. The identifying assumption of local randomization would be violated if people are able to control the birth quarter around the threshold (McCrary 2008, Lee and Lemieux 2010). But the institutional background of this study excludes the possibility of manipulation, since parents were unable to anticipate the policy change in 1990 and manipulate the birth month of their children in 1983. Appendix Figure B1 also demonstrates that the distribution of birth quarter is smooth around October 1983.

4.5.2 Covariates Balance

RD approach requires the smoothness of the distribution of the covariates across the threshold. Otherwise, the RD estimates of treatment effects may actually reflect the

Table 4-3: RD estimation results (College Completion)

	Local Linear Regression		Second Order Global Polynomial Regression			
	(1)	(2)	(3)	(4)	(5)	(6)
	IK Bandwidth Selector	CCT Bandwidth Selector	6-Year Window (without covariates)	4-Year Window (without covariates)	6-Year Window (with covariates)	4-Year Window (with covariates)
Overall	0.011	0.014	0.004	0.007	0.003	0.004
	(0.009)	(0.010)	(0.009)	(0.010)	(0.008)	(0.010)
N	25728	20789	59542	39270	59542	39270
Males	0.005	0.011	0.001	-0.005	-0.002	-0.011
	(0.014)	(0.015)	(0.014)	(0.017)	(0.014)	(0.017)
N	10820	8938	23007	14978	23007	14978
Females	0.014	0.013	0.005	0.014	0.007	0.014
	(0.012)	(0.014)	(0.011)	(0.013)	(0.010)	(0.012)
N	15874	12798	36535	24292	36535	24292
Whites	0.016	0.018	0.012	0.012	0.011	0.011
	(0.012)	(0.014)	(0.011)	(0.013)	(0.011)	(0.013)
N	16258	13118	37333	24637	37333	24637
Hispanics	-0.027**	-0.025	-0.026**	-0.036***	-0.026**	-0.036***
	(0.013)	(0.015)	(0.011)	(0.013)	(0.011)	(0.013)
N	6148	4237	15242	10247	15242	10247
Blacks	-0.006	-0.006	-0.011	-0.023	-0.014	-0.025
	(0.018)	(0.021)	(0.015)	(0.018)	(0.015)	(0.018)
N	4323	3387	11027	7355	11027	7355
Asians	-0.036	-0.004	-0.054	-0.050	-0.064	-0.049
	(0.052)	(0.078)	(0.058)	(0.073)	(0.057)	(0.073)
N	1914	836	2969	1828	2969	1828

Notes: Standard errors are reported in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

discontinuous change in the other characteristics across the eligibility threshold. Thus we examine whether the respondents' characteristics, including marital status, gender and race/ethnicity, reveal discontinuous changes in density around the cutoff point. In this regard, we estimate the local linear model using gender, marital status, and race/ethnicity as dependent variables respectively. Since these variables should be as-good-as random around the threshold, we should not observe significant discontinuities in those predetermined characteristics across the threshold. As shown in Appendix Table B1 and Appendix Figure B2, the results for covariate balance tests suggest little evidence of discontinuities of those characteristics. Although the RD estimates suggest somewhat slight discontinuities for distribution of males and Asian under nonparametric specifications, these effects are only marginally significant at the 10 percent level. We do not believe this reflects a systematic discontinuity of covariates on the two sides of the eligibility threshold. Even if there was weak evidence that Asian had a propensity to sort to the right side of the eligibility threshold, our results would not be changed, since RD estimates do not find significant impact of Medicaid on educational achievement of Asians.

4.5.3 Falsification Tests

We conducted falsification tests using the fourth quarter of 1982 instead of the fourth quarter of 1983 as the cutoff point in the RD design. The purpose of the tests is to exclude the age effect (specific age to enter school) on educational achievement that may confound the effect of Medicaid. Since there are some age requirements to enter school varying by states and schools, an individual born in August 1983 could enter school almost one year earlier than an individual born in October 1983. It is necessary to make sure that there are no significant treatment effects from this ‘pseudo’ cutoff point where the eligibility did not experience a discontinuous change. We show the estimates from the local linear models on high school completion and college completion for the overall sample and all the subsamples in Appendix Table B2. As expected, there are no significant discontinuities of high school or college completion around the ‘pseudo’ cutoff point. Therefore, we exclude the possibility that our results from RD design are driven by the other confounding factors other than Medicaid.

4.6 Discussion

4.6.1 Previous Related Literature

As briefly mentioned in the introduction, the previous literature provides substantial evidence that health welfare programs improve health care utilization and health outcomes. Moreover, enrollment in public health insurance can translate into improvements in well-being by adding more disposable family income. With insurance premium support from local Medicaid managed care, enrollees can potentially avoid costly medical expenditures and out-of-pocket expenses in case of suffering a serious illness. It also prevents personal bankruptcy under some extreme circumstances (Card and Shore-Sheppard 2004, DeLeire et al. 2013, Cohodes et al. 2014).

However, there are also some potential negative impacts of welfare programs that need to be considered. A number of empirical studies have evaluated the treatment effects of disability insurance programs on human capital accumulation and labor force participation. For example, Chen and Van der Klaauw (2008) find that the labor force participation rate of disability insurance beneficiaries would have been 20 percentage points higher at most if the beneficiaries had not received these benefits during the

1990s. Von Wachter et al. (2011) and Maestas et al. (2013) find even larger estimates of negative impacts of Social Security Disability Insurance on employment. Similar results are also found in French and Song (2014) and Autor et al. (2015).

While disability insurance programs cover a limited segment of the population, there is also a growing literature examining the causal effect of Medicaid on labor supply. An early study by Moffitt and Wolfe (1992) finds a negative impact of Medicaid on labor supply. However, based on the Oregon Medicaid experiment of 2008 that recruited adults from uninsured low-income families and randomly assigned them into a treatment and a control group, Baicker et al. (2013) found that Medicaid enrollment caused a modest but not significant reduction of employment in the short term (i.e., two years). In contrast, Garthwaite et al. (2013) and Dague et al. (2014) find that Medicaid enrollment caused a sizable reduction in employment in Tennessee and Wisconsin. With a particular interest in single mothers, Strumpf (2011) finds no evidence of Medicaid on labor supply of single mothers.

Despite inconsistent findings about the impact of Medicaid enrollment on labor activities, there is a general consensus that public welfare programs do not always provide incentives to work, and in some cases significant disincentives to work outweigh incentives.

Our study adds to this literature by providing plausibly causal estimates of the negative effects of Medicaid on educational achievement in the long term through a RD design. We believe that some effects might not appear when enrollees are young but work gradually through the enrollee's adolescence. Thus, our study supports the argument in Murray (1984) that welfare programs may inhibit work ethic and human capital accumulation.

4.6.2 Moral Hazard and Disincentive from Health Welfare Programs

The negative impact of Medicaid found in our analysis can be potentially explained from the perspective of moral hazard in the health insurance market (Ehrlich and Becker 1972, Shavell 1979, Zweifel and Manning 2000). For example, moral hazard arises when people change their lifestyle in unhealthy ways after having health insurance. Some evidence suggests that health insurance enrollment is associated with negative life style choices such as heavy smoking and obesity (Stanciole 2008), since after obtaining insurance, people lose the incentive to be on healthy diets, do physical activities or workout. The main idea of emphasizing moral hazard in our discussion is to explore behavioral aspects in the context of social health care program, which are not limited to health behavior but also related to economic and educational behaviors. Medicaid participants know that even if they lost their job or got a serious illness in the future, they would be 'covered', and thus have less incentive to implement preventions or work hard to generate precautious savings.

According to Zweifel and Manning (2000): "*Ex ante moral hazard depends importantly on the opportunity cost of preventive effort, which in many instances is approximately proportional to the wage rate*" (Chapter 8, P.418). High school completion usually makes a difference in wages and income. However, the gains might not be high enough to incentivize people to pursue graduation from high school. Since

OBRA 1990 regulates that all children and adolescents under the age 19 from families with income below 100% of the poverty line are entitled to participate in Medicaid, eligible children and adolescents can benefit from the policy as long as they qualify for the family income requirements. In contrast, higher family income reduces eligibility for enrollment in the program. The increase in family income may not be enough to compensate the loss from disqualification for Medicaid. Thus, another possible interpretation for the negative effects of Medicaid on high school completion is that the income threshold for Medicaid eligibility erodes the work ethic of parents from low-income families and encourages them to remain in poverty to qualify for Medicaid at the expense of their child's educational investment in the long term.

4.6.3 Difference between High School and College Education

Another key finding of this study is that Medicaid enrollment affects high school completion rate but has little impact on college completion rate in general (except for Hispanics). A plausible interpretation relies on a cost-benefit analysis. Education decision making involves tradeoffs between present value of perceived benefits in the future and current investment costs (Becker 1962, Mincer 1974, Perna 2000). Although the expected return to college education overweighs the benefits from Medicaid by staying in poverty, the expected return to high school education may not be large enough to overcome moral hazard and disincentive in health care programs.

4.6.4 Heterogeneity among Racial/Ethnic Groups

Our analysis emphasizes the heterogeneous impacts of Medicaid on educational attainments by race/ethnicity.[13] In particular, we find that Hispanics are more adversely affected by Medicaid on high school completion than other racial/ethnic groups, and the negative impact of Medicaid on college completion is significant only among Hispanics. These results draw interests to explore the underlying mechanism for the racial/ethnic heterogeneity associated with socioeconomic factors. Because of a large scale immigration from Latin America, many Hispanics are nonnative-born and have low English proficiency (Morales et al. 2002). Due to the disadvantages in socioeconomic status and language barriers, a large proportion of Hispanics are restricted to low-wage work such as agriculture and construction. In this case, disposable family income of Hispanic families are relatively low, leading to higher opportunity costs for education and lower expected return to education. These adverse conditions may prevent Hispanics from efficiently utilizing health care services, which further traps them in the welfare programs and inhibit their educational outcome.

4.7 Conclusion

Medicaid is an important public health care program for low-income families in the United States. Despite substantial studies evaluating its impact on health outcomes, little is known about its effects on educational achievement in the long term. To empirically

[13] We do not find consistent gender differences under different model specifications. Therefore, gender difference is not discussed here.

explore the causal effect of Medicaid participation on educational achievements, we exploit a regression discontinuity design that takes advantage of a plausible exogenous variation created by the Medicaid expansion of 1990. This article presents evidence that Medicaid enrollment decreases high school completion rate on average. With respect to heterogeneous effects by race/ethnicity, we find that Medicaid enrollment reduced high school completion rates for Hispanics and whites, but not for blacks and Asians. Regarding college completion, only Hispanics were negatively affected by Medicaid enrollment.

The results of this paper add to the long-standing debate surrounding the impacts of social welfare programs. Although the mechanism through which Medicaid functions remains unclear, we presume that the short-term gains from Medicaid enrollment may erode the incentive to study and work, and thus leaving participants in an undesirable economic situation in the long term. Hence it is important to further explore how the mechanism of the social welfare program works in the context of education. For future social health care program design, policy makers should consider the function that promotes education and work incentives. Recent research in psychology and economics suggest that "nudges" have cost-effective and persistent effects on welfare gains and rational choices (Thaler and Sunstein 2008). A default education savings account may be a helpful "nudging" option. Moreover, to make the welfare recipients better evaluate the cost and benefit of the programs, the information about the cost and benefit of the welfare programs should be more visible, simple, and informative.

The findings of our study also shed light on directions for future research. With more details about how people adjust their decisions on human capital accumulation in response to Medicaid expansion, one can conduct a structural analysis to deepen our understanding of the underlying mechanism. We also expect large-scale controlled field experiments to find more cost-effective ways to encourage the welfare recipients increase investment and efforts in education.

5 CONCLUSIONS

This dissertation conducts an econometric evaluation of an obesity intervention program, after school physical activities and a nationwide social health care program. In chapter 2, I evaluated the peer effects in the context of TGEG, a childhood obesity intervention program. Using data from the intervention program, I outlined the effects of dietary behavior and physical activity on students' BMI. In general, strong peer effects were found for the full sample and for both female and male students. Simultaneously, I classified students into *improvement* and *non-improvement* groups based on their BMI categorization changes over time. However, the peer effect for female students was only found among students in the improvement group; and for male students, it was only found among those in the non-improvement group. I attempted to explain heterogeneous effects from behavioral and physiological character traits of children in terms of forming a social group and interacting with their peers in the group. These findings shed light on how peer influence can affect physical fitness levels in different groups of students. This knowledge can be instructive for designing curriculum, extracurricular activities and intervention measures in the future. Moreover, it can help inform special measures for the group of students who could not benefit from peer influence; such measures might include paring students in this group with positive peer role-models.

The second essay in chapter 3 investigated the impact of after school physical activities on the math and science test scores of students using 2011 TIMSS survey. Results indicated that playing after school increased students' math scores by approximately 7.9 points, and it increased science scores by approximately 4.2 points. The increases in math and science scores were higher with greater parental involvement. Lower parental involvement resulted in a lesser increase in math scores and no effect on science test scores. In general, this finding identified parental involvement as a key component in childhood intervention programs. For example, in order to boost the positive effects, parents are encouraged to be more involved in supervising after school activities of their children. Schools can also provide more guidance to parents on how to play an active role in guiding their children during after-school activities.

The third essay in chapter 4 examined the long term effects of Medicaid enrollment on educational attainment using a regression discontinuity design. I took advantage of OBRA 1990 as a natural experiment. A convincing source of random variation was created through the discontinuous change in the Medicaid eligibility of OBRA 1990. In order to obtain a robust result, I predefines a 24-birth-quarter window, in which case respondents born six years before and after the cutoff line were included in the analysis. I further restricted the sample using 100%, 138% and 150% of the federal poverty line as a robustness check, and the results were consistent. My results indicated that Medicaid enrollment decreased high school completion rates. Although there is a limitation of the mechanism that links Medicaid enrollment and participants' education attainments, this study provides some evidence of the causal relationship between these two variables. The findings suggest that policy makers should focus on improving labor and education incentives.

Although this dissertation conducts an economic analysis using causal effect methods and solid identification strategies, each essay has limitations and could be improved upon in future research.

In chapter 2, TGEG was targeted at Title I schools and conducted in four different counties of Texas. These schools were characterized by a high percentage of students from low income families. The study can be extended outside of Texas, but special attention is required when generalizing these findings to other states. All the heterogeneity in students, teachers and schools should be considered for the analysis of peer effects in other states in the future.

In chapter 3, the dissertation focused on fourth grade students. Future research could extend the current work to the evaluation of middle school students. I believe that, during different stages of childhood/ adolescence, after school activities may influence students in different ways. The interaction between parental involvement/supervision and the effect of after school activities might also vary at different stages of development.

For chapter 4, since I do not have program participation information traced back to 1990, I estimated an intent-to-treat effect. The next step is to explore a more detailed dataset that links information of Medicaid enrollees today and their Medicaid enrollment information dating back to 1990. I could, for instance, attempt to provide a more comprehensive explanation of the mechanism through structure modelling. The variables of interest could then be extended to labor market activities, health care and family income.

This dissertation demonstrated the application of causal effect methods in analyzing the effect of health related policy/program on educational attainment. At the same time, I showed the limitations of these methods. In the future, I will continue the current research in health related area and extent it using more advanced models, such as structural model.

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APPENDIX A

APPENDIX FOR SECTION 3

Table A-1: Treatment effects of playing after school for student whose parents make sure children set aside time for homework.

Matching Algorithm	NNM		CRM		KM	
General	Math	Science	Math	Science	Math	Science
ATT	5.374**	3.514	7.510***	4.549***	7.468***	4.511***
	(2.232)	(2.105)	(1.680)	(1.584)	(1.644)	(1.745)
N	7819	7819	7819	7819	7819	7819
Females						
ATT	7.910***	5.974*	8.772***	5.962***	8.627***	5.843***
	(3.154)	(2.945)	(2.090)	(2.321)	(2.045)	(2.152)
N	4065	4065	4065	4065	4065	4065
Males						
ATT	7.576***	7.178**	5.331**	2.169	5.257**	2.119
	(3.471)	(3.505)	(2.421)	(2.340)	(2.386)	(2.324)
N	3754	3754	3754	3754	3754	3754
Whites						
ATT	10.951***	8.840***	13.120***	10.141***	13.152***	10.097***
	(3.272)	(2.833)	(2.428)	(2.090)	(2.239)	(2.189)
N	4025	4025	4025	4025	4025	4025
Hispanics						
ATT	-1.416	-0.548	-6.473**	-7.172**	-6.451*	-7.148**
	(4.402)	(4.450)	(2.840)	(3.131)	(2.798)	(3.065)
N	1990	1990	1990	1990	1990	1990
Blacks						
ATT	5.813	5.114	0.163	-2.316	0.292	-2.039
	(7.087)	(7.316)	(2.840)	(3.131)	(4.672)	(5.470)
N	829	829	829	829	829	829
Asians						
ATT	-16.079	-10.688	-3.147	-2.741	-3.013	-2.631
	(10.693)	(11.803)	(7.462)	(8.011)	(7.887)	(8.638)
N	350	350	350	350	350	350

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table A-2: Playing after school vs not playing after school for student whose parents do not make sure children set aside time for homework.

Matching Algorithm	NNM		CRM		KM	
General	Math	Science	Math	Science	Math	Science
ATT	6.514	2.036	8.152**	1.012	8.085**	0.945
	(4.857)	(5.134)	(3.387)	(3.510)	(3.228)	(3.313)
N	2053	2053	2053	2053	2053	2053
Females						
ATT	9.208	2.751	10.652***	4.608	10.512**	4.603
	(7.434)	(7.703)	(4.856)	(4.885)	(4.917)	(5.026)
N	916	916	916	916	916	916
Males						
ATT	0.886	-3.186	7.049	-0.636	7.092	-0.485
	(6.231)	(6.604)	(4.636)	(4.790)	(4.564)	(4.516)
N	1137	1137	1137	1137	1137	1137
Whites						
ATT	10.425*	0.676	9.698**	1.111	9.659**	1.108
	(6.773)	(6.750)	(5.069)	(5.163)	(4.558)	(4.975)
N	1013	1013	1013	1013	1013	1013
Hispanics						
ATT	2.420	-2.858	4.385	1.546	4.472	1.647
	(8.812)	(9.627)	(6.278)	(6.286)	(5.735)	(6.903)
N	530	530	530	530	530	530
Blacks						
ATT	-5.970	-13.970	-9.434	-11.295	-9.106	-11.348
	(15.623)	(18.488)	(14.217)	(14.414)	(13.007)	(15.505)
N	218	218	218	218	218	218
Asians						
ATT	3.788	-1.945	-4.251	-11.284	-3.357	-9.810
	(24.737)	(21.497)	(18.515)	(18.132)	(19.157)	(17.740)
N	127	127	127	127	127	127

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table A-3: Playing after school vs not playing after school for student whose parents check their children's homework.

Matching Algorithm	NNM		CRM		KM	
General	Math	Science	Math	Science	Math	Science
ATT	11.108***	8.311***	8.920***	5.445***	8.799***	5.327***
	(2.425)	(2.295)	(1.610)	(1.661)	(1.546)	(1.702)
N	7654	7654	7654	7654	7654	7654
Females						
ATT	9.915***	5.359	10.187***	6.331***	10.041***	6.204***
	(2.862)	(3.010)	(2.297)	(2.212)	(2.104)	(2.212)
N	3956	3956	3956	3956	3956	3956
Males						
ATT	9.023***	4.897	7.691***	4.209*	7.558**	4.039**
	(3.321)	(3.655)	(2.589)	(2.398)	(2.307)	(2.618)
N	3698	3698	3698	3698	3698	3698
Whites						
ATT	13.582***	10.820***	15.656***	10.879***	15.671***	10.858***
	(3.312)	(3.127)	(2.373)	(2.316)	(2.385)	(2.452)
N	3945	3945	3945	3945	3945	3945
Hispanics						
ATT	-3.028	0.216	-4.385	-3.915	-4.419	-4.001
	(4.622)	(4.830)	(3.248)	(3.082)	(2.989)	(3.168)
N	1878	1878	1878	1878	1878	1878
Blacks						
ATT	-4.495	-5.031	0.280	-1.266	0.449	-1.090
	(6.504)	(8.030)	(5.335)	(5.490)	(4.603)	(5.650)
N	852	852	852	852	852	852
Asians						
ATT	-8.774	-1.739	-1.884	3.034	-1.804	2.769
	(10.937)	(12.376)	(7.747)	(7.416)	(7.351)	(7.977)
N	347	347	347	347	347	347

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
* *p*<0.1, ** *p*<0.05, *** *p*<0.01

Table A-4: Playing after school vs not playing after school for student whose parents do not check their children's homework.

Matching Algorithm	NNM		CRM		KM	
General	Math	Science	Math	Science	Math	Science
ATT	3.932	-0.904	1.576	-4.050	1.545	-4.078
	(4.250)	(4.993)	(3.071)	(3.272)	(3.113)	(3.235)
N	2283	2283	2283	2283	2283	2283
Females						
ATT	0.917	-0.558	2.086	-1.193	2.056	-1.323
	(6.053)	(6.065)	(4.624)	(4.009)	(4.251)	(4.689)
N	1055	1055	1055	1055	1055	1055
Males						
ATT	3.408	-3.208	4.141	-4.001	4.091	-3.998
	(6.130)	(6.131)	(4.478)	(4.649)	(4.168)	(4.574)
N	1228	1228	1228	1228	1228	1228
Whites						
ATT	2.806	-1.087	3.354	-0.316	3.368	-0.289
	(6.151)	(6.556)	(4.395)	(4.747)	(4.259)	(4.597)
N	1124	1124	1124	1124	1124	1124
Hispanics						
ATT	-1.362	-7.357	0.634	-5.030	0.442	-5.485
	(8.107)	(7.792)	(5.281)	(5.305)	(5.421)	(5.196)
N	652	652	652	652	652	652
Blacks						
ATT	-7.713	-11.326	-13.046	-24.245	-12.273	-23.670*
	(17.602)	(17.459)	(15.921)	(14.774)	(14.094)	(13.751)
N	208	208	208	208	208	208
Asians						
ATT	2.800	-10.063	17.665	6.090	17.171	4.907
	(20.711)	(22.753)	(18.398)	(18.472)	(18.407)	(18.658)
N	131	131	131	131	131	131

Notes: Bootstrap standard errors based on 200 iterations are reported in parentheses.
* *p*<0.1, ** *p*<0.05, *** *p*<0.01

APPENDIX B

APPENDIX FOR SECTION 4

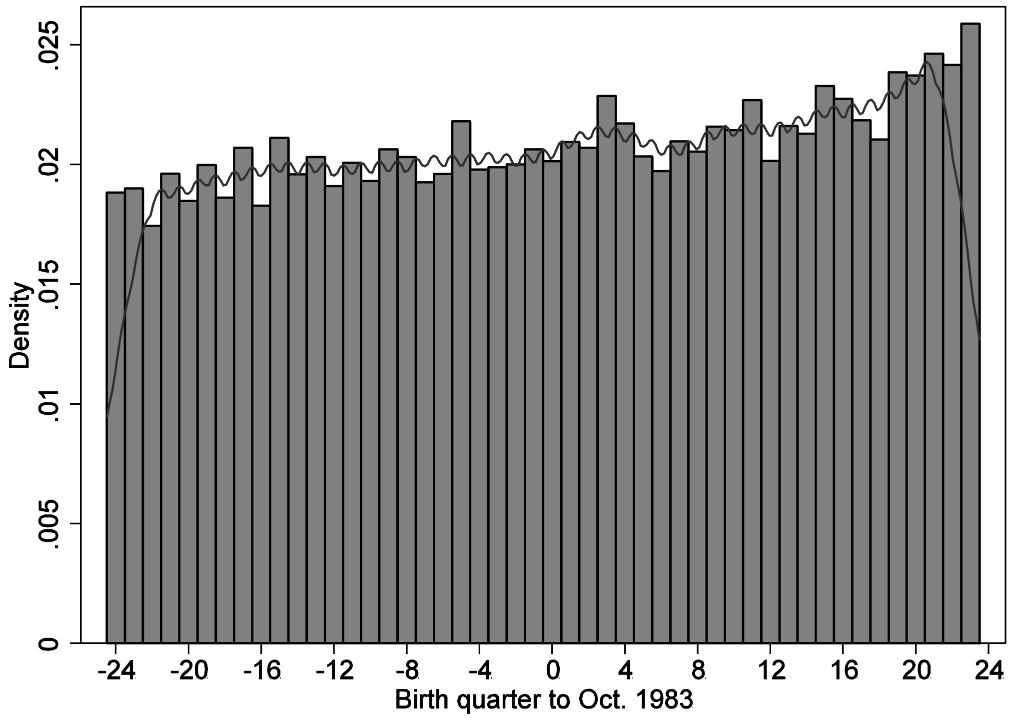

Figure B-1: Histogram and kernel density, birth quarter

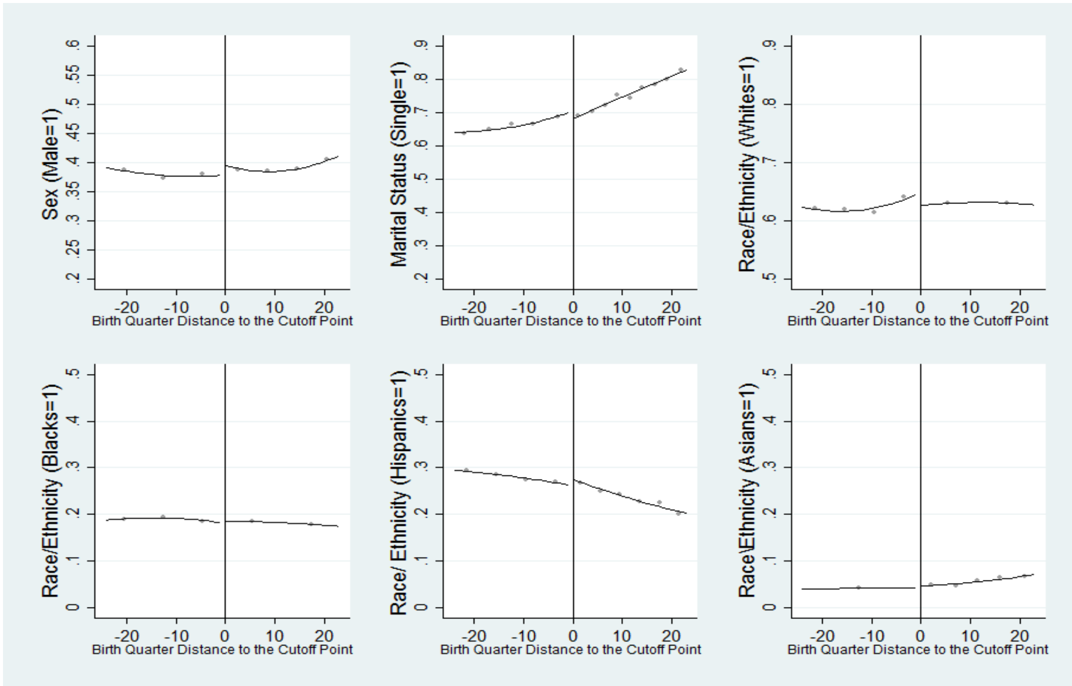

Figure B-2: Covariates balance check

Table B-1: Covariates balance check

	Local Linear Regression	
	IK Bandwidth Selector	CCT Bandwidth Selector
Gender (male=1)	0.022*	0.022*
	(0.013)	(0.013)
N	28274	28274
Marital Status (single=1)	-0.018	-0.018
	(0.015)	(0.015)
N	23302	23302
Race (Whites=1)	-0.013	-0.009
	(0.013)	(0.015)
N	28274	20789
Ethnicity (Hispanics=1)	0.018	0.018
	(0.012)	(0.012)
N	28274	28274
Race (Blacks=1)	-0.002	-0.002
	(0.01)	(0.01)
N	28274	28274
Race (Asians=1)	0.009*	0.012*
	(0.006)	(0.006)
N	25728	20789

Notes: Standard errors are reported in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table B-2: Falsification test

	High School Completion		College Completion	
	IK Bandwidth Selector	CCT Bandwidth Selector	IK Bandwidth Selector	CCT Bandwidth Selector
Overall	-0.013	-0.015	0.004	-0.002
	(0.011)	(0.012)	(0.008)	(0.010)
N	32736	27908	32736	18213
Males	-0.016	-0.015	-0.009	-0.011
	(0.017)	(0.020)	(0.011)	(0.018)
N	14362	10649	17092	6980
Females	-0.018	-0.027	0.009	0.005
	(0.015)	(0.017)	(0.010)	(0.012)
N	15733	12749	18709	12749
Whites	0.001	-0.007	0.008	0.002
	(0.014)	(0.017)	(0.009)	(0.013)
N	18930	14463	22009	11497
Hispanics	0.013	0.013	0.002	0.003
	(0.018)	(0.030)	(0.011)	(0.015)
N	13787	5615	8795	4924
Blacks	-0.009	0.003	0.008	0.004
	(0.022)	(0.028)	(0.016)	(0.021)
N	7053	4734	5682	3394
Asians	-0.038	-0.033	0.042	0.049
	(0.047)	(0.057)	(0.055)	(0.068)
N	1446	1032	1571	1126

Notes: Standard errors are reported in parentheses.
* p<0.1, ** p<0.05, *** p<0.01