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DO NEIGHBORHOOD PARKS AND PLAYGROUNDS REDUCE CHILDHOOD OBESITY?

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ABSTRACT:

Promoting physical activity in children is an important front battling Childhood obesity. This paper investigates if and by how much neighborhood parks and playgrounds, one of the most important activity-enhancing neighborhood facilities, affect childhood obesity. We employ a covariate matching technique to analyze the 2007 National Survey of Children Health data. We find that neighborhood parks and playgrounds make children more fit. The reduction in body mass index (BMI) as well as the overweight or obesity risk is both statistically and economically significant. We also find that the park impact depends on gender, age, race, income, neighborhood safety, and other neighborhood amenities. The results suggest that a provision of neighborhood parks and playgrounds is likely to make children more fit, but relevant interventions need to take socioeconomic status of the targeted children population as well as other neighborhood amenities into consideration.

KEYWORDS: CHILDHOOD OBESITY, NEIGHBORHOOD AMENITY, PARK/PLAYGROUND, MATCHING

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The prevalence of childhood obesity in the United States has risen dramatically across all racial, gender, and ethnic groups since 1980 (Dehghan, Akhtar-Danesh and Merchant, 2005; Hedley et al., 2004; Ogden et al., 2006). The prevalence of obesity doubled among preschoolers aged 2-5 and tripled among children and adolescents aged 6-19 from 1976-1980 to 2007-2008 (CDC, 2010). By 2007-2008, approximately two out of ten children (19.6%) and adolescents (18.1%) were obese. The increasing rate of childhood obesity has significantly negative health, psychological, and social consequences due to impaired quality of life and increased morbidity (Must and Strauss, 1999; Reilly et al., 2003). Compared with normal-weight children, obese children are at a higher risk for chronic diseases such as cardiovascular diseases, bone and joint abnormalities, and sleep apnea (Daniels et al., 2005; General, 2009; Lobstein, Baur and Uauy, 2004; Speiser et al., 2005) as well as for being obese as an adult (Guo and Chumlea, 1999; Guo et al., 2002; Parsons et al., 1999). Furthermore, obesity imposes adverse effects on cognitive, social, and psychological development in children (Garner et al., 1976; Must and Strauss, 1999) and has long lasting negative impacts on adult health, employment, and socioeconomic status (Case, Fertig and Paxson, 2005).

Obesity results from an energy imbalance involving too much caloric intake and/or insufficient physical activities. Lakdawalla and Philipson (2002) find that much of the increase in body weight over the 20th century is due to decreased physical activity, largely from workers moving away from physically demanding jobs and toward sedentary ones. The 2009 National Youth Risk Behavior Survey (NYRBS) conducted among 9th through 12th graders in both public and private schools in the United States reports that 23% of students did not participate in at least 60 minutes of physical activity on at least one day during a period of seven days before the survey (NYRBS, 2009). The notion of "obesogenic environment" has been proposed and modeled to investigate how the built environment and socio-economic deprivation at the community level affect childhood obesity (Caballero, 2007; Egger and Swinburn, 1997; Papas et al., 2007; Poston and Foreyt, 1999). Among all the factors incorporated in the models of obesogenic environment, availability and access to neighborhood amenities (i.e. physical facilities) is regarded as one of the most important elements affecting childhood obesity and has gained increasing attention in primary prevention (Koplan, Liverman and Kraak, 2005; Papas et al., 2007; USDHHS, 2001). The literature has documented a positive association between a higher level of physical activity and the density of neighborhood recreational facilities (McInnes and Shinogle, 2009) or their proximity and attractiveness (Yancey et al., 2007). This study focuses on neighborhood parks and playgrounds as they provide physical locations for outdoor physical activities among children. They are one of the important activity-enhancing community facilities to fight the childhood obesity epidemic and help children establish a physically active lifestyle. Furthermore, adding a park/playground in a neighborhood is a relatively feasible policy intervention in the battle against childhood obesity.

The goal of this paper is to understand how important neighborhood parks and playgrounds affect childhood obesity and how characteristics of neighborhoods and individuals affect the neighborhood park effect. More specifically, we estimate the effects of having a neighborhood park/playground on childhood obesity and body mass index (BMI) and examine how other neighborhood amenities and safety as well as socioeconomic characteristics such as age, gender, race, and income affect the park effect. We use the 2007 National Survey of Children Health (NSCH) for the empirical analysis. The 2007 NSCH survey collected information on neighborhood characteristics, particularly, the existence of parks/playgrounds, sidewalks/pathways, and community centers/kids' clubs in each respondent's neighborhood. It also collected a rich set of socioeconomic information about the respondents. Apparently, the respondents are not randomly assigned to neighborhoods with different amenities. From the policy perspective, it is either impractical or too costly to assign individuals to neighborhood with different amenities. Thus, we face an endogeneity problem in evaluating the effect of neighborhood parks/playgrounds on obesity using the cross-sectional data because a health-conscious individual may self-select into a neighborhood promoting physical activities. To address the selection problem, we use covariate matching that allows us to avoid the possible misspecification errors and the weak instrument variables required by parametric methods, such as Heckman selection model.

We find that neighborhood parks/playgrounds make children more fit. The reduction in BMI and obesity is both statistically and economically significant. We also find that the effect depends on gender, age, race, income, neighborhood safety, and other neighborhood amenities. The average treatment effect is greater for girls than boys, younger cohorts aged 10-13 than adolescents aged 14-17, non-Hispanic Whites than Blacks and Hispanics, children in low-income households, and children living in a perceived unsafe neighborhood than children living a perceived safe neighborhood. Community centers and kids' clubs attenuates the neighborhood park effect on both boys and girls, but sidewalks/pathways enhance (attenuates) the park effect on boys (girls).

LITERATURE REVIEW

Previous studies in the public health literature support the associations between access to neighborhood amenities and more outdoor physical activities and/or less sedentary activities

(Bedimo-Rung, Mowen and Cohen, 2005; Cohen et al., 2006; Gordon-Larsen et al., 2006; Grow et al., 2008; Norman et al., 2006; Roemmich et al., 2006; Timperio et al., 2004; Veugelers et al., 2008). Living in a neighborhood with walkable, connected sidewalks and crosswalks, large density of different types of destinations such as schools, stores, and parks, and high levels of connectivity between destinations is found to be associated with an increase in physical activities. However, the effectiveness of neighborhood amenities on physical activities depends significantly on neighborhood safety because the concern of neighborhood safety might decrease residents' willingness to engage in outdoor physical activities and curbs active commuting (e.g. bicycling). Furthermore, residing in an unsafe neighborhood may also increase stress and result in less active living style (Björntorp, 2001; Roemmich et al., 2007), especially when exposed to neighborhood violence (Kliewer, 2006).

Though the association between neighborhood amenities and physical activities is well established in the literature, the relationship between neighborhood amenities and obesity is less clear. Some studies find that neighborhood amenities are related to lower prevalence of overweight or obesity (Gordon-Larsen et al., 2006; Veugelers et al., 2008), but others find no statistically significant relationship (Burdette and Whitaker, 2004; Norman et al., 2006). Using the Children's Lifestyle and School-performance Study of Canada, Veugelers et al. (2008) find children in neighborhoods with good access to playgrounds, parks, and recreational facilities are reportedly more active and less likely to be overweight or obese. Using a survey of low-income preschoolers living in Cincinnati, Ohio, Burdette and Whitaker (2004) find that proximity to playgrounds is not related to the prevalence of being overweight.

Economic studies that investigate the causal link between neighborhood environment and childhood obesity are sparse. Kling et al. (2007) take advantage of the Moving to Opportunity (MOT) program to investigate the neighborhood effect on adult health and obesity. The MOT program is a randomized housing mobility experiment in which families living in a distressed poor neighborhood in five cities (Baltimore, Boston, Chicago, Los Angeles, and New York) were randomly offered vouchers to move to private housing units in a lower-poverty neighborhood. They find a significant reduction in the adult obesity prevalence for the treated group relative to the control group. However, such a program is expensive. Kling et al. (2007) do not identify the specific contributing neighborhood factors in the obesity reduction, which limits its practical relevance to interventions. Sandy et al. (2009) combine data on recreational trails and violent crimes with anthropomorphic and diagnostic data from children's clinic visits in Indianapolis between 1996 and 2005 to study the effects of urban environment on childhood obesity. They assume that any change in neighborhood amenities were exogenous to children who stayed at the same address prior and post the change. They find that the arrival of amenities are unrelated to children's BMI, but physical facilities, such as fitness areas and volleyball courts, lead to statistically significant weight reduction among eight-year old boys. In a closely related paper, Sandy et al. (2010) find that the presence of a trail nearby reduces children's weight, but the nearby violent crime rate may undermine the trail effect. They attribute the credibility of the trail effect to two facts: 1) the location of trails is likely to be exogenous due to the fact that trails follow river banks and abandoned railways; and 2) trails were unlikely to be factored into the house location choice among families as there was very limited time between their announcement and construction. However, as they admitted, families may self-select into neighborhood with different levels of neighborhood crime.

Overall, the literature on childhood obesity focusing on environmental factors investigates the association rather than causality and offers conflicting results. The documented statistical associations between childhood obesity and neighborhood amenities are not adequate to establish a causal relationship and provide policy implications given the possibility of self-selection (Ewing, Brownson and Berrigan, 2006; Plantinga and Bernell, 2007; Sandy et al., 2009). The built environment can be associated with obesity through either self-selection or environmental determinism (Ewing, 2005). That is, individuals who want to be physically active may select an environment that promotes physical activities (self-selection); or a good environment causes individuals to become more physically active than they would be otherwise, therefore reducing the risk of being overweight and obese (environmental determinism). This paper focuses on causal relationships between neighborhood parks/playgrounds and childhood obesity.

METHODOLOGIES

Traditionally, the treatment effect on dependent variable, Y_i, is estimated in parametric models with a dummy variable, which classifies units (e.g. individuals) into the treated and comparison (control) groups. For instance, we may estimate the following equation:

(1) $Y_i = X_i^{'}\beta + \alpha T_i + \varepsilon_i$

where $T_i = 1(0)$ if individual i is treated (untreated), X_i is a vector of observed characteristics, and ε_i is unobserved random error. Under the assumption that $E(\varepsilon_i \mid X_i, T_i) = 0$, the standard ordinary least square (OLS) estimator is unbiased and consistent, and the estimate of α is the average treatment effect. However, when assignment to the treated group is not random (i.e. $E(\varepsilon_i | X_i, T_i) \neq 0$), the OLS estimator is biased and inconsistent due to endogeneity .

The common econometric approaches dealing with endogeneity include the Heckman's two-step treatment model and instrumental variable regression. Although both approaches have been popular, they entail a few major difficulties. First, they need to satisfy an identification requirement. That is, we must have at least one variable that is not included in X_i affecting the treatment status, but is not correlated with ε_i. However, it is difficult (sometimes impossible) to find such instrument variables to meet the identification requirement. In the absence of such an exclusion restriction, the model is not identified. Second, the so-called LaLonde's (1986) critiques suggest that non-experimental estimates are sensitive to model specification, and differ greatly from the experimental estimates.

This paper employs matching estimator to identify and quantify the casual impacts of neighborhood parks/playgrounds on children obesity. Matching techniques have distinct advantages over other non-experimental evaluation techniques. First, matching does not impose any specific functional form between the dependent variable and independent variables, thus avoiding possible model misspecification errors (Rosenbaum and Rubin, 1983). Second, matching could impose a common support requirement. The poor overlap in support between the treated and the comparison groups raises questions about the robustness of parametric methods relying on functional form to extrapolate outside the common support (Dehejia and Wahba, 1998; Smith and Todd, 2005). Third, matching allows endogenous covariates (Caliendo and Kopeinig, 2008).

Denote Y_{1i} the outcome if individual i is treated and Y_{0i} the outcome if individual i is not treated. Ideally, the treatment effect is the difference of outcomes between the treated and comparison groups, $Y_{1i} - Y_{0i}$. Three types of average treatment effects are defined:

$$\text{(2)} \qquad \text{Treatment Effects} = \begin{cases} ATE = E[Y_{1i} - Y_{0i}] & \text{for the population;} \\ ATT = E[Y_{1i} - Y_{0i} \mid T_i = 1] & \text{for the treated group;} \\ ATC = E[Y_{1i} - Y_{0i} \mid T_i = 0] & \text{for the comparison group.} \end{cases}$$

However, the above treatment effects are not observable due to a missing data problem: being in the treated group Y_{1i} conceals the other potential outcome Y_{0i} and vice versa.

In a purely randomized experiment, a difference-in-difference estimator would give unbiased estimates of the treatment effect. However, randomly assigning neighborhood characteristics is either impractical or too expensive. The average treatment effect at the population level can be estimated without bias by either experimental data or observational data if the selection bias is only due to observables. In observational studies, matching uses the observables to adjust for possibly confounded treatment assignments by regrouping observations. One underlying assumption of the matching estimators is that all the variables driving self-selection are observable to researchers, and that the assignment to the treatment is independent of outcomes conditional on covariates (so called ignorability i.e. Rosenbaum and Rubin, 1983). The following two assumptions are critical for the matching estimator:

A1. Conditional Independence Assumption: $(Y_0, Y_1) \perp T \mid X$; and

A2. Common Support Assumption: $0 < prob(T = 1 \mid X) < 1$;

where $\perp$ is the notation for statistical independence. Assumption **A1** says that all the variables driving self-selection are observable to researchers, i.e., the assignment to the treatment is independent of outcomes conditional on covariates (LaLonde, 1986). Assumption **A2** says that the probability of participation in treatment is bounded between zero and one. Take the average treatment effect for the treated (*ATT*) as an example. Under **A1** and **A2** we have

$$\begin{aligned} ATT &= E_{x|T=1}\{E[Y_1 \mid T=1, X=x] - E[Y_0 \mid T=1, X=x]\} \\ &= E_{x|T=1}\{E[Y_1 \mid T=1, X=x] - E[Y_0 \mid T=0, X=x]\} \end{aligned} \tag{3}$$

Equation (3) shows that we can estimate ATT since the unbiased estimates of $E[Y_1 \mid T=1, X=x]$ and $E[Y_0 \mid T=0, X=x]$ can be estimated based on the data. Similarly, we can also estimate treatment effects for the comparison group (*ATC*) and for the population (*ATE*).

There are two major types of matching techniques: propensity score matching (PSM) and covariate matching (CVM). This paper employs the CVM for the following reasons. First, the CVM is able to incorporate sampling weights into estimation, while there is no practical method of including sampling weights in PSM. Second, crucial variables such as age, gender, and race require exact matching because comparing an 11-year old with a 15-year old, a female with a male, or an African-American with a Latino-American, is likely to lead to bias in estimates. However, such exact matching is feasible only in CVM. Third, it is difficult to balance the estimated distributions of the propensity score between the treated and the comparison groups in our data set given the fact that most respondents live in a neighborhood with a park/playground (77.29% of more than forty thousand respondents).

Covariate Matching

The basic idea of CVM is to impute counterfactual outcomes for program participants using untreated individuals with similar values of pretreatment covariates.[1] If the decision to take the treatment is "random" for individuals with similar values of the pretreatment variables or covariates, we can use the average outcome of some similar individuals who were not exposed to the treatment as the counterfactual outcome for each individual. Intuitively, comparing two individuals with the same predetermined characteristics, where one is treated and the other is not, is like comparing those two individuals in a randomized experiment.

To estimate ATT, the CVM estimator matches every treated individual to a number of individuals in the comparison group with similar socio-economic characteristics that are correlated to the treatment status and/or the outcome. The choice of the matched individuals in the comparison group is based on the distance measured by the vector norm $\|\cdot\|$. Let $\|x\|_V = (x'Vx)^{1/2}$ be the vector norm with positive definite matrix V.[2] The CVM defines $\|z-x\|_V$ as the distance between the vector x and z, where x and z represent the covariates for a treated unit and a potential match. Let $d_M(i)$ be the distance from individual i to the M^{th} nearest match with the opposite treatment status. It is formally defined as $\sum_{l:T_l=1-T_i} 1\left\{\|X_l - X_i\|_V \le d_M(i)\right\} = M$, where $1\{\cdot\}$ is the indicator function, which is equal to one when the value in brackets is true and zero otherwise; and X_i and X_l are characteristics for the individual i and the matched individual l. The set of individuals that individual i matches with is $\Psi_M(i) = \left\{l = 1,\ldots,N \middle| T_l = 1-T_i, \|X_l - X_i\|_V \le d_M(i)\right\}$. We denoted the estimated outcome by $\hat{Y}_{0i}$ if not treated and $\hat{Y}_{1i}$ if treated. The treatment effects defined in Eq. (2) becomes:

$$
(4)\quad \text{Treatment Effects} = \begin{cases} ATE = \dfrac{\sum_i \left(\hat{Y}_{1i} - \hat{Y}_{0i}\right)}{\sum_i (1 - T_i) + T_i} & \text{for the population;} \\ ATT = \dfrac{\sum_{i|T_i=1} \left(Y_{1i} - \hat{Y}_{0i} \middle| T_i = 1\right)}{\sum_i T_i} & \text{for the treated group;} \\ ATC = \dfrac{\sum_{i|T_i=0} \left(\hat{Y}_{1i} - Y_{0i} \middle| T_i = 0\right)}{\sum_i 1 - T_i} & \text{for the comparison group.} \end{cases}
$$

The simple matching estimator will be biased in finite samples when the matching is not exact. (Abadie and Imbens, 2011) develop a bias-corrected matching estimator adjusting the difference within the matches for the differences in their covariate values. They show that, with *k* continuous covariates, the estimators will have a term corresponding to the matching discrepancies (the difference in covariates between matching individuals and their matches) that will be of the order $O_p\left(N^{-1/k}\right)$. They propose a non-parametric bias-adjustment to render the estimates $N^{1/2}$ consistent. The bias-corrected matching estimator adjusts the difference within the matches for the differences in their covariate values. The adjustment is based on an estimate of the two regression functions: $\mu_t(x) = E\{Y(t) | X = x\}$ for $t = 0$ or 1. The regression functions are approximated by linear functions and estimated using least squares on the matched observations: $\hat{\mu}_t(x) = \hat{\beta}_{t0} + \hat{\beta}'_{t1}x$ for t=0 or 1, where $\left(\hat{\beta}_{t0}, \hat{\beta}_{t1}\right) = \arg\min_{\{\beta_{t0}, \beta_{t1}\}} \sum_{i:T_i=t} K_M(i)\left(Y_i - \hat{\beta}_{t0} - \hat{\beta}'_{t1}x\right)$

and $K_M(i) = \sum_{l=1}^{N} 1\left\{ i \in \Psi_M(l) \dfrac{1}{\#\Psi_M(l)} \right\}$ that is the number of times individual *i* is used as a match for all observations *l* of the opposite treated group, each time weighted by the total number of matches for observations *l*. Observations in these regressions are weighted by $K_M(i)$, the number of times the unit is used as a match, because the weighted empirical distribution is closer to the distribution of covariates in which we are ultimately interested. For this reason, only the matched sample is used in this step; using the full sample would include observations sufficiently different from our sample of interest. Given the estimated regression functions, for the bias-corrected matching estimator of CVM predicts the missing potential outcomes as:

$$\tilde{Y}_i(0) = \begin{cases} Y_{0i} & \text{if } T_i = 0 \\ \frac{1}{\#\Psi_M(i)} \sum_{l \in \Psi_M(i)} \left(Y_l - \hat{\mu}_0(X_i) - \hat{\mu}_0(X_l) \right) & \text{if } T_i = 1 \end{cases} \tag{5}$$

The corresponding bias-corrected average treatment effect can be estimated by replacing $\hat{Y}_{0i}$ with $\tilde{Y}_i(0)$ in equation (5). Specifically, the bias-corrected estimator for the average treatment effect on the treated is $\text{Bias Corrected ATT} = \frac{1}{N_1} \sum_{i|T_i=1} \left(Y_i(1) - \tilde{Y}_i(0) \right)$.

Although theoretically matching on multidimensional covariates can lead to substantial bias, matching combined with bias adjustment often leads to estimates with little remaining bias.

DATA AND DIAGNOSIS ANALYSIS

The paper uses the 2007 NSCH data, which contains a nationally representative random sample of households in each of the 50 states and the District of Columbia. The survey is designed to examine the physical and emotional health of children from birth up until age 17. If a sampled household has more than one child, a child is randomly chosen as a sampled child based on the complete roster of children in the household. The 2007 NSCH collected a rich set of demographic, health, family, school, neighborhood and community information.

In particular, three questions are asked about different types of neighborhood amenities: 1) Does a park or playground area exist in your neighborhood? 2) Do sidewalks or walking paths exist in your neighborhood? and 3) Does a recreation center, community center, or boys' or girls' club exist in your neighborhood? We create three binary variables for these three neighborhood amenities (1=answer yes to the questions, 0 otherwise).

The paper focuses on children aged 10-17 because only 44,015 individuals aged 10-17 out of all 91,532 individuals surveyed were asked to report both weight and height from which BMI is calculated. BMI, as the most popular measurement to determine childhood overweight and obesity, is a reasonable indicator of body fatness for most children and teens. However, researchers find that that children's body composition, as well as their BMI, changes substantially with age and between genders (Cole, Freeman and Preece, 1995; Cole et al., 2000; Dietz and Bellizzi, 1999; Rolland-Cachera et al., 1982). Therefore, using 25 and 30 of BMI as cut-off points for being overweight and obese for children of all ages and both genders is problematic. An alternative method, z-score, is based on age- and gender-specific reference percentiles for BMI. It is more precise to determine a child's weight status and has been used widely. In this paper, overweight and obesity are defined as at or above the 85th and 95th percentile of age- and gender-specific BMI.[3] Additionally, the z-score has two advantages. First, it is consistent with adult index for being overweight and obese, so it can be used continuously from two years of age to adulthood, and it tracks being overweight in childhood into adulthood. Second, it also provides internationally acceptable cut off points for BMI for being overweight and obese in children, which makes country comparison on childhood obesity practical and more precise (Cole et al., 2000). These two advantages of z-score are less important for our study as it is not cross-country analysis and does not link to the adult obesity status.

The sampling weights for the 2007 NSCH are constructed to avoid bias from a choice-based sample and become national representative (see (Blumberg et al., 2007) for details). Unless noted otherwise, the results reported in the paper are weighted. **Table 1** presents the prevalence of overweight and obesity for different demographic groups. It shows that the overweight and obesity rates in our sample are consistent with the national level – 35.74% and 17.89% for the pre- and early adolescent group (19,999 individuals aged 10-13), and 25.56% and 11.97% for the adolescent group (24,816 individuals aged 14-17). **Table 1** also shows the BMI and the prevalence of overweight or obesity is higher among boys than girls, among Hispanic and Black children than non-Hispanic white children, and among those living below 133% of the federal poverty level than those living above it. The student t tests reported in **Table 1** show that the weight difference by age cohorts, gender, race, and income is statistically significant at the 1% level. Table 2 compares the prevalence of being overweight and obese between neighborhoods with and without different types of physical facilities. As shown in Table 2, a neighborhood with amenities such as playgrounds and parks, sidewalks and pathways, or community centers and kids' clubs, or perceived as a safe neighborhood is associated with lower BMI, as well as a lower prevalence of being overweight or obese. The differences in the weight measure between neighborhoods with and without a particular amenity are statistically significant at the 5% level with an exception of sidewalks and pathways. We also compare distributions of BMI between children living in a neighborhood with and without a park/playground. Figure 1 suggests a gender-invariant pattern – children living in neighborhoods with a park/playground have a lower probability of being overweight or obese based on the kernel density estimates of BMI. Figure 1 also separates the respondent into different cohorts by age, race and income level of which the similar pattern exists.

Given that the objective of the paper is to estimate the park effect on childhood obesity and how the park effect is affected by characteristics of individuals and their neighborhoods, we perform the diagnosis test of the mean difference of weight measures. Let $\overline{Y}_{k,p=1}$ and $\overline{Y}_{k,p=0}$ denote the mean weight measure *k* (*k* = BMI, overweight, and obesity) among the respondents who indicate that a park/playground exists in their neighborhood (*p* = 1) or not (*p* = 0), respectively. The mean difference of the weight measure between samples with and without neighborhood parks/playgrounds can be written below:

(6) $$\overline{DY}_k^j = \left(\overline{Y}_{k,p=1} \mid X_j = 1\right) - \left(\overline{Y}_{k,p=0} \mid X_j = 1\right)$$

where X_j indicates a certain characteristic of individual (*j* = *G* for gender, *j* = *C* for age cohort, *j* = *E* for race, and *j* = *L* for whether living below 133% of the Federal poverty level) or of their neighborhood (*j* = *S* for sidewalks/pathways; *j* = *R* for kids' clubs/community centers; and *j* = *M* for perceived neighborhood safety). We plot $\overline{DY}_k^j$ for all *j*'s and *k*'s in Figure 2. The shape of the markers in Figure 2 represents a certain characteristic of individuals or their neighborhoods -- – circles for the base of individual characteristics or the presence of a certain neighborhood characteristics, and triangles for the corresponding counterparts. A solid marker suggests that the mean difference between samples with and without neighborhood parks and playgrounds is statistically significant at the 10% level and a hallow marker indicates insignificant differences.

Figure 2 suggests that neighborhood parks/playgrounds are associated with a lower BMI and a low overweight or obesity risk, which is represented by the negative mean difference of weight measures between samples with and without parks/playgrounds. Furthermore, Figure 2(a) shows that the differences in BMI and the prevalence of overweight or obesity are greater for girls than boys, among young age cohort than older children, and for non-Hispanic white children than black and Hispanic children, as well as among children in low income households in the case of obesity or overweight risk. However, the difference is not necessarily statistically significant. The left two panels of Figures 2(b) shows that the mean difference of weight measure between samples with and without parks/playgrounds varies by the existence of sidewalks/pathways as well as community centers/kids' clubs, but such difference is not statistically significant. The NSCH respondents were also asked to state their perception of neighborhood safety by answering the question, "How often do you feel the surveyed child is safe in your community or neighborhood?" Respondents were given four choices: Never, Sometimes, Usually, and Always. We classify a safe neighborhood if the respondents answered "Always" and a non-safe neighborhood if the respondents answered "never" or "sometimes." The right panel of Figure 2(b) suggests that a neighborhood park/playground is associated with a greater, statistically significant reduction in BMI and the prevalence of being overweight in perceived unsafe neighborhoods.

The summary statistics and diagnosis tests discussed above suggest that (a) both BMI and the prevalence of being overweight or obese differ significantly by age, gender, race, household income level, and the existence of neighborhood amenities; and (b) the potential impact of neighborhood parks/playgrounds vary by different socio-demographic groups, perceived neighborhood safety level, and availability of other neighborhood amenities.

MATCHING: STRATEGIES AND RESULTS

We focus on the average treatment effects of neighborhood parks/playgrounds on the comparison group (*ATC*) because understanding the potential park effect on childhood obesity in neighborhoods without this particular amenity has practical policy implications. The average treatment effect on the comparison group can be written as:

$$(7) \qquad (P_1): ATC_p = E(Y_{1i} - Y_{0i} \mid p_i = 0)$$

SELECTION OF MATCHING VARIABLES AND THE BALANCE TEST

Implementing covariate matching requires choosing a set of matching variables. No statistical algorithms or rules are available to choose a set of variables that satisfy the identification condition of matching estimators. However, there are three generally agreed rules of thumb. First, variables that have been affected by the treatment should not be used as matching covariates. Second, not all relevant variables should be matching covariates if the sample size of the treatment or comparison group is small. Third, covariates that are not correlated, or weakly correlated with outcome or the treatment indicators, may exacerbate the common support problem and result in large variances (Imbens, 2004).

We match on male and female subsamples separately because of the following three reasons. First, males and females experience quite different metabolism processes and body development when they are teenagers and adolescents (Tarnopolsky, 1999). Second, neighborhood amenities may affect males and females differently. For example, (Gomez et al., 2004) find that neighborhood safety increases the level of physical activities and reduces childhood obesity among girls, but not boys. Carver et al. (2008) find that that outdoor physical activities among adolescent children are associated with different neighborhood amenities – the presence of traffic and pedestrian lights for adolescent girls, and residing on a cul-de-sac and/or the presence of speed bumps for boys. Third, the data set is sufficiently large to do match separately on males (N = 22,906) and females (N = 21,109).

Our selection of matching covariates depends on theoretical considerations, regression analyses, and data availability. Table 3 lists all matching covariates we use in five groups. First, socio-demographic information group includes age, and race for both genders and whether born in U.S. for males. We expect that age and ethnic characteristics would be correlated with the unobserved biological differences affecting BMI. BMI is found to be highly age-dependent among children and adolescents (Cole, Freeman and Preece, 1995; Cole et al., 2000; Rolland-Cachera et al., 1982). Ethnic background is a good way to control for genetic factors in a cross-section data set. Since age and ethnicity are two extremely important BMI-determining variables, we match age and ethnicity backgrounds precisely. Second, health information group includes children's general health status and teeth condition for both genders and whether having a depression problem for females. Third, physical activities related information group includes television watching time, whether having a TV in the bedroom, and weekly exercise time for both genders, as well as whether participating in after-school sports for females. Fourth, parental and family information group consists of mother's education level, mother's health status, whether mother born in the U.S., and family income level for both genders, as well as the total number of kids in the family for males. Parental and household information is important. For example, mother's educational level and birth place would be a proxy for awareness of nutrition and diet habit.

We would expect family income level and number of children to reflect the unobserved information about household's resource and intra-household allocation. Fifth, perceived neighborhood characteristics includes whether having sidewalks/pathways, whether having community centers and kids' clubs, a variable indicating how often people help each other in the neighborhood, and the perceived neighborhood safety level.

The first thing to check before doing matching is the overlap situation of the matching variables between the treated group and the comparison group. Lack of overlap can result in poor matches and bias in estimates. Based on the histogram for each matching variable by the treatment status, all selected matching variables have good overlap between the treated group and the comparison group.[4] The crucial conditional independence assumption of matching is not testable. One practical way of evaluating the matching quality is to compare the characteristics before and after matching and check if matching eliminates, or significantly decreases differences between the treated group and the comparison group. That is, for each matching model, we compare the mean difference of each matching variable between the treated groups and the comparison group before and after matching. For an ideal match, the mean differences of all matching variables that are statistically significant before matching become insignificant and the size of the differences become smaller after matching.

The Overall Treatment Effects of Neighborhood Parks and Playgrounds

This section presents our main matching results on male and female subsamples separately, where the subsamples are also exactly matched on gender, age, and race in additional to the other matching variables discussed above. Figure 3 plots the average treatment effects of neighborhood parks and playgrounds on weight status for the comparison group. The left scale is for BMI measured by the unit (kg/m^2). The right scale is for the probability of being overweight or obese measured by percentage points. The results strongly suggest that neighborhood parks/playgrounds could make children more fit as they decrease BMI as well as the risk of being overweight or obese. The impacts are stronger on females than males. More specifically, neighborhood parks/playgrounds could reduce the probability of being overweight or obese by approximately three percentage points for males, and five to six percentage points for females.

To check if matching has done a good job, for each matching covariate, we compare the mean of the treated group with the mean of the comparison group before and after matching. For each matching variable, we report the mean differences between the treated group and the comparison group before and after matching as well as the p-values of t-statistics in Table 3.[5] The results show a clear lack of balance for unmatched samples: 19 (16) of 23 mean differences for males (females) are statistically significant at the 5% level. Matching improves the balance significantly. After matching, the number of mean differences of statistical significance reduces to 10 for both males and females. Among these 10 covariates of which mean differences are still statistically significant, 6 (7) of them have smaller differences after matching for females (males). However, the balance is not perfect after matching. First, the statistically significant mean difference still exists after matching. Second, for children's health condition, exercise time and number of kids in the household, and whether people help each other in the neighborhood, either became statistically significant, or the size became greater after matching. The imperfect match is largely due to the imposed precise match on age and ethnic background. Precisely matched variables (e.g., gender, age, and race) can cause mismatches on other matching variables by being weighted

1,000 times more than other regular matching variables.

To show the size of the impact, we divide the treatment effects by the corresponding sample means of the weight status among the comparison group and calculate the percentage change. The results show that neighborhood parks/playgrounds could decrease BMI and the probability of being overweight or obese by 1%, 9%, and 23% for males.[6] The corresponding numbers for females are even greater, namely 2%, 17%, and 28%. We conclude that the overall effects of neighborhood parks/playgrounds are both statistically and economically significant; the effects are greater for females than for males.

DOES THE TREATMENT EFFECT DEPEND ON CONDITIONS OF OTHER AMENITIES?

We expect that the impacts of a park/playground on child weight status depend on the other amenities in the same neighborhood because different amenities could be substitutes or complements to children for outdoor physical activities. The 2007 NSCH data allow us to examine how sidewalks/pathways as well as community centers/kids' clubs in the neighborhood influence the neighborhood park effect. To achieve this goal, we estimate ATC_P based on four subsamples with different combinations of two other neighborhood amenities. Consequently, the following treatment effects are estimated:

$$(P_2): ATC_p = E(Y_{1i} - Y_{0i} \mid P_i = 0,\ S_i = 1)$$
$$(P_3): ATC_p = E(Y_{1i} - Y_{0i} \mid P_i = 0,\ S_i = 0)$$
$$(P_4): ATC_p = E(Y_{1i} - Y_{0i} \mid P_i = 0,\ R_i = 1)$$
$$(P_5): ATC_p = E(Y_{1i} - Y_{0i} \mid P_i = 0,\ R_i = 0)$$

P_2 (P_3) represents the treatment effect of parks/playgrounds on weight status when sidewalks/pathways are (not) available in the same neighborhood. Similarly, P_4 (P_5) represents the treatment effect of parks/playgrounds when community centers/kids' clubs are (not) available in the same neighborhood. The comparisons between P_2 and P_3, as well as between P_4 and P_5, allow us to investigate whether other neighborhood amenities enhance or attenuate the impacts of neighborhood parks/playgrounds.

Figure 4 plots the treatment effects P_2 to P_5. The results clearly show that the presence of other amenities affects the impacts of neighborhood parks/playgrounds. In the case of neighborhood sidewalks/pathway, for boys the treatment effects are statistically insignificant when a park/playground coexists with sidewalks/pathways, but become statistically significant and greater in magnitude when a park/playground does not exist (P_2 vs. P_3 for males). This means that sidewalks/pathways attenuate the treatment effects of neighborhood parks/playgrounds for boys. The situation differs for girls. More specifically, the reduction in the overweight or obesity risk is approximately doubled when a park/playground coexists with sidewalks/pathways (P_2 vs. P_3 for females). However, the results on BMI are not consistent with that for the overweight or obesity risk for girls. That is, an absence of neighborhood sidewalks/pathways is associated with a statistically significant, greater park effect, but the park effect is not statistically significant otherwise. The above results may suggest that parks/playgrounds and sidewalks/pathways are more likely to be complements than substitutes for girls. The comparison between P_4 and P_5 shows that the community centers and/or kids' clubs attenuates the effect of neighborhood parks/playgrounds for both girls and boys. This suggests that neighborhood parks/playgrounds and community centers are likely to be substitutes.

DOES THE PERCEIVED SAFETY LEVEL AFFECT THE TREATMENT EFFECTS?

As we discussed in section 2, neighborhood safety may play an important role in the usage of neighborhood amenities and affect males and females differently. The impact of safety on the effects of neighborhood amenities is far from clear mainly because neighborhood safety is a complex concept including, but not limited to, diverse components such as traffic safety (Alton et al., 2007; Hume et al., 2009; Mullan, 2003; Valentine and McKendrck, 1997), personal injury, bullying, harm from strangers (Alton et al., 2007; Timperio et al., 2004), and threats of interpersonal violence (Carver, Timperio and Crawford, 2008). We re-estimate the treatment effect for the comparison group on safe and unsafe subsamples. The safe subsample includes those who thought that their neighborhood were "always" safe (55.25% of whole sample). The unsafe subsample includes those who thought that their neighborhoods were "never" or "sometimes" safe (9.28% of whole sample).

Figure 5 plots the treatment effects based on these two subsamples. It shows that providing a park/playground could lead to a greater reduction in BMI and the probability of being overweight or obese for both boys and girls in an unsafe neighborhood relative to a safe neighborhood. The only exception is for the risk of obesity for boys. Furthermore, the differences of the park effect between safe and unsafe neighborhoods are more significant for females than males. Therefore, building neighborhood parks/playgrounds in an unsafe neighborhood can be more effective in helping children stay fit than in a safe neighborhood. The possible reason can be that neighborhood parks/playgrounds are important physical locations for children in unsafe neighborhoods, but children in a safer neighborhood may have other outlets for outdoor physical activities.

DOES THE TREATMENT EFFECT DIFFER BY RACIAL AND ETHNIC GROUPS?

There are significant racial and ethnic disparities in obesity prevalence among U.S children and adolescents (CDC, 2010). According to the NHANES 2007-2008, among adolescents aged 12-19 Mexican-American boys have the highest prevalence of obesity (28.6%) followed by non-Hispanic black boys (19.8%) and non-Hispanic white boys (16.7%). And non-Hispanic black girls have the highest prevalence of obesity (29.8%) followed by with Mexican-American girls (17.4%) and non-Hispanic white girls (14.5%). The 2007 NSCH also provides evidences for racial and ethnic disparities in obesity prevalence. As shown in Table 1, the prevalence of obesity among Hispanic and black children aged 10-17 is 21.66%, a rate double that for non-Hispanic white children (11.40%). And the prevalence of overweight for non-Hispanic white children is only 2/3 of that for Hispanics and blacks (39.72% vs. 25.75%). Furthermore, the NHEANS data for 1988-1994 and 2007-2008 suggest that the racial and ethnic disparities in the prevalence of obesity widened in 2007-2008 (CDC, 2010). The prevalence of obesity increased by 79% among non-Hispanic girls and 63% among non-Hispanic white girls. During the same periods, the growth rate of the obesity prevalence doubled among Mexican-American and non-Hispanic black boys (85-90%) compared to non-Hispanic white boys (44%). Based on these statistics, policy interventions targeting Hispanic and black populations are more urgent than other racial groups in combating the childhood obesity epidemic.

We re-estimate the treatment effects on black and Hispanic subsample and non-Hispanic white subsample and plot the results in Figure 6. The park effects are negative, statistically significant in all weight measures for non-Hispanic white children. The magnitude of the impact on boys is approximately 2 to 3 times as large as that on girls. However, the treatment effects for Hispanic and black children are not as large and significant as that for non-Hispanic white children. Results show that a neighborhood park/playground could reduce the probability of being obese among girls and increase BMI of boys without making them more overweight or obese. Even though results show that the policy intervention targeting non-Hispanic white children is expected to be more effective, we cannot ignore the significance of helping minority children given the fact that Hispanic and Black children have much higher obesity rates than non-Hispanic white children.

Does Income Affect the Treatment Effects?

The causal effects of neighborhood amenities are likely to be different for children with different household income levels. The 2007 NSCH collects household income information in terms of categories outlined by different federal poverty levels. We divide the 2007 NSCH sample into two subsamples, below and above 133% of the federal poverty level, which is frequently used as a threshold for income eligibility for receiving food and nutrition subsidies through the National School Lunch Program, School Breakfast Program, and Supplemental Nutrition Assistance Program. As shown in **Table 1**, compared with those with household income level above 133% of the federal poverty level, respondents with household income level below 133% of the federal poverty level have a little bit higher BMI (22.86 vs. 21.29), but much higher overweight and obesity rates (42.32% vs. 26.94% and 24.18% vs. 12.05%).

Matching results of two subgroups are plotted in Figure 7. We find that the treatment effect on obesity among those with household income below 133% of the federal poverty level is more than double than among those with household income above 133% of the federal poverty level. This finding together with the fact that the prevalence of being overweight and obese is documented to be significantly greater among the low-income population provides support for intervention targeting those with low socioeconomic status.

ARE THE TREATMENT EFFECTS AGE-SPECIFIC?

Due to different metabolism processes and different patterns of physical activities among children of different age, neighborhood parks/playgrounds might affect different age groups differently. Estimating the treatment effect for each age year separately can be problematic because matching requires a large amount of observations to get a precise match and the sample size of each age year subgroups is too small. Thus, we divide the sample into two subgroups, the pre- and early adolescents aged 10-13 and adolescents aged 14-17, and re-estimate the treatment effects.

We plot the estimates in Figure 8. The results show the treatment effects are stronger, and more statistically significant among the younger cohort aged 10-13 than the cohort aged 14-17, and that the effects are larger among females than males in the younger cohort. Among the older cohort aged 14-17, we find that the treatment effects on being overweight and obese are both negative and significant for females, and that only the treatment on overweight is negative and significant for males. In conclusion, a neighborhood park/playground could be more beneficial to younger children, especially young girls.

CONCLUSIONS AND POLICY IMPLICATIONS

Stopping and reversing the childhood obesity epidemic requires promoting active lifestyle and increasing energy expenditures. Welcoming neighborhood physical facilities such as parks and playgrounds provides incentives for outdoor activities. However, it is necessary to build the evidence about how to intervene. Our paper estimates the causal effect of neighborhood parks/playgrounds on childhood obesity; it also investigates how the causal effect attenuated or enhanced by other neighborhood characteristics and whether the magnitude of the causal effect depends on demographic and economic factors.

The results suggest that adding a park/playground to a neighborhood could reduce the obesity rate and make children more fit. The reduction in BMI as well as the probability of being overweight or obese is both statistically and economically significant. We also find: 1) the causal impact is gender-dependent – on average the impact is greater among girls than boys, 2) the impact is age-specific – the average treatment effect is greater among the younger cohort aged 10-13 compared with those aged 14-17 for both gender groups, 3) the impact is race-specific – non-Hispanic white youth benefit from neighborhood parks and playgrounds much more than blacks and Hispanics, 4) the effect is greater among children in unsafe neighborhoods than those living in safe neighborhoods, 5) the impact depends on the income level – children living above 133% of the federal poverty level are more likely to benefit from neighborhood parks/playgrounds, but the magnitude of the effect is greater among those living below the 133% of the federal poverty level if it is statistically significant, and 6) the impact depends on other neighborhood amenities – the existence of community center/kids' club attenuates the effect of parks/playground among both boys and girls— but sidewalks/pathways enhance (attenuate) the treatment among boys (girls).

The results suggest the provision of neighborhood parks/playgrounds is likely to make children more fit. Although building a park/playground is relatively simpler than other policy interventions such as taxing high-fat and high-calorie foods to alter eating habits, it has not been officially declared as a method to fight childhood obesity. Furthermore, interventions need to consider socioeconomic status of the targeted children population as well as other neighborhood amenities.

Inspired by the park effect found in this study, we envision future research to document and analyze the level and frequency of physical activities conditional on current neighborhood as well as the potential increases in physical activities if neighborhood amenities are provided. Such analyses require measures of actual physical activities in neighborhood physical facilities and at home and school to control for substitution. Unfortunately, such information is not available in the NSCH data. We leave this research question on how to promote an active lifestyle for future research pending on available data and/or funding for field experiments.

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Table 1. Weight Status and Equal Mean Tests by Age, Gender, Race, and Income Level

	BMI		Overweight (%)		Obese (%)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Total sample	21.66	0.06	30.40	0.59	14.79	0.47
Young cohort: 10-13 (N=19,999)	20.69	0.10	35.74	0.87	17.89	0.73
10	19.61	0.18	38.42	1.75	20.28	1.46
11	20.86	0.27	38.44	1.84	20.92	1.65
12	20.75	0.17	33.18	1.76	16.67	1.51
13	21.48	0.15	33.34	1.60	14.06	1.15
Old cohort: 14-17 (N=24,816)	22.55	0.08	25.56	0.78	11.97	0.60
14	21.70	0.14	26.03	1.46	11.79	1.00
15	22.35	0.14	25.63	1.26	11.84	0.90
16	23.07	0.19	27.32	1.76	13.33	1.53
17	23.15	0.16	23.05	1.66	10.86	1.16
Equal mean test ($U_{young\ cohort} - U_{old\ cohort}$)	t = -14.46***		t = 8.61***		t = 6.36***	
Female (N=21,109)	21.45	0.09	27.10	0.84	11.61	0.62
Male (N=22,906)	21.87	0.09	33.65	0.81	17.92	0.70
Equal mean test ($U_{male} - U_{female}$)	t = 3.26***		t = 4.98***		t = 5.90***	
Hispanic/Black (N=8,787)	22.75	0.14	38.98	1.34	20.88	1.10
Non-Hispanic white (N=31,012)	21.19	0.07	26.26	0.60	12.10	0.50
Equal mean test ($U_{Hispanic/Black} - U_{white}$)	t = 9.73**		t = 9.81***		t = 8.72***	
Household income relative to the 133% of the Federal poverty level						
Under (N=5,690)	22.90	0.16	41.54	1.46	22.73	1.19
Above (N=34,805)	21.37	0.08	27.88	0.67	12.81	0.53
Equal mean test ($U_{Under} - U_{Above}$)	t = 8.61***		t = 9.71***		t = 8.80***	

Asterisks (***, **, and *) stand for statistically significance at the 1%, 5%, and 10% level, respectively.

Table 2. Weight Status and Equal Mean Tests by Neighborhood Characteristics

	BMI		Overweight (%)		Obese (%)	
Neighborhood Characteristics	No	Yes	No	Yes	No	Yes
Parks/playgrounds	21.94	21.59	33.15	29.63	16.22	14.41
(Yes/No)	(0.13)	(0.08)	(1.18)	(0.68)	(0.90)	(0.55)
Equal mean test ($U_{no} - U_{yes}$)	$t=2.42^{**}$		$t=2.88^{***}$		$t=2.06^{**}$	
Sidewalks/pathways	21.78	21.62	30.99	30.18	16.36	14.23
(Yes/No)	(0.12)	(0.08)	(0.93)	(0.73)	(0.80)	(0.57)
Equal mean test ($U_{no} - U_{yes}$)	t=1.19		t=1.20		$t=2.41^{**}$	
Kids' clubs /community centers	21.84	21.55	32.55	29.28	15.99	14.05
(Yes/No)	(0.12)	(0.08)	(0.99)	(0.74)	(0.80)	(0.58)
Equal mean test ($U_{no} - U_{yes}$)	$t=2.05^{**}$		$t=3.19^{***}$		$t=2.68^{***}$	
Perceived neighborhood safety	22.48	21.67	35.90	30.45	19.23	14.95
(safe vs. unsafe)	(0.21)	(0.09)	(1.76)	(0.82)	(1.39)	(0.65)
Equal mean test ($U_{unsafe} - U_{safe}$)	$t=3.61^{***}$		$t=3.22^{***}$		3.26^{***}	

Asterisks (***, **, and *) stand for statistically significance at the 1%, 5%, and 10% level, respectively.

Table 3. Balancing Tests of Matching Covariates

		Females		Males	
		Difference[a]	p>|t	Difference[a]	p>|t|
Social-demographic information of children					
Age (year)	Unmatched	0.12***	0.00	0.04	0.29
	Matched	0.00	1.00	0.00	1.00
Non-Hispanic White (yes/no)	Unmatched	0.05***	0.00	0.06***	0.00
	Matched	0.00	1.00	0.00	1.00
Hispanic (yes/no)	Unmatched	-0.03***	0.00	-0.02***	0.00
	Matched	0.00	1.00	0.00	1.00
Black (yes/no)	Unmatched	-0.01*	0.04	-0.02***	0.00
	Matched	0.00	1.00	0.00	1.00
Other race (yes/no)	Unmatched	0.00	0.40	-0.01***	0.00
	Matched	0.00	1.00	0.00	1.00
Child born in the U.S. (yes/no)	Unmatched	NA	NA	0.01***	0.00
	Matched	NA	NA	0.00	0.88
Children's health information					
Health condition of the child	Unmatched	0.05***	0.00	0.02	0.17
(from 1=excellent to 5=poor)	Matched	0.10***	0.00	0.08***	0.00
Teeth (1=good; 0=bad)	Unmatched	-0.01	0.12	-0.01***	0.00
	Matched	-0.01	0.12	-0.01	0.30
Child having a depression problem	Unmatched	0.00	0.81	NA	NA
(yes/no)	Matched	0.00	0.46	NA	NA
Physical activity related information of children					
Television watch time (minute)	Unmatched	5.31***	0.00	1.93	0.29
	Matched	9.95***	0.00	9.44***	0.00
A TV set in the kid's bedroom (yes/no)	Unmatched	0.05***	0.00	0.05***	0.00
	Matched	0.01	0.27	-0.01	0.27
Exercise time (minute)	Unmatched	-0.13	0.00	-0.13***	0.00
	Matched	-0.11*	0.02	-0.20***	0.00
Take after-school sports lessons	Unmatched	-0.04***	0.00	NA	NA
(yes/no)	Matched	-0.03*	0.02	NA	NA
Parental and household information					
Mother's education below high school	Unmatched	0.01*	0.04	0.01**	0.01
(yes/no)	Matched	0.01	0.26	0.01	0.23
Mother's education above high school	Unmatched	0.04***	0.00	0.05***	0.00
(yes/no)	Matched	0.02*	0.02	0.02**	0.01
Mother's health condition	Unmatched	0.11***	0.00	0.11***	0.00
(from 1=excellent to 5=poor)	Matched	0.09***	0.00	0.09***	0.00
Mother born in the U.S. (yes/no)	Unmatched	0.03***	0.00	0.04***	0.00

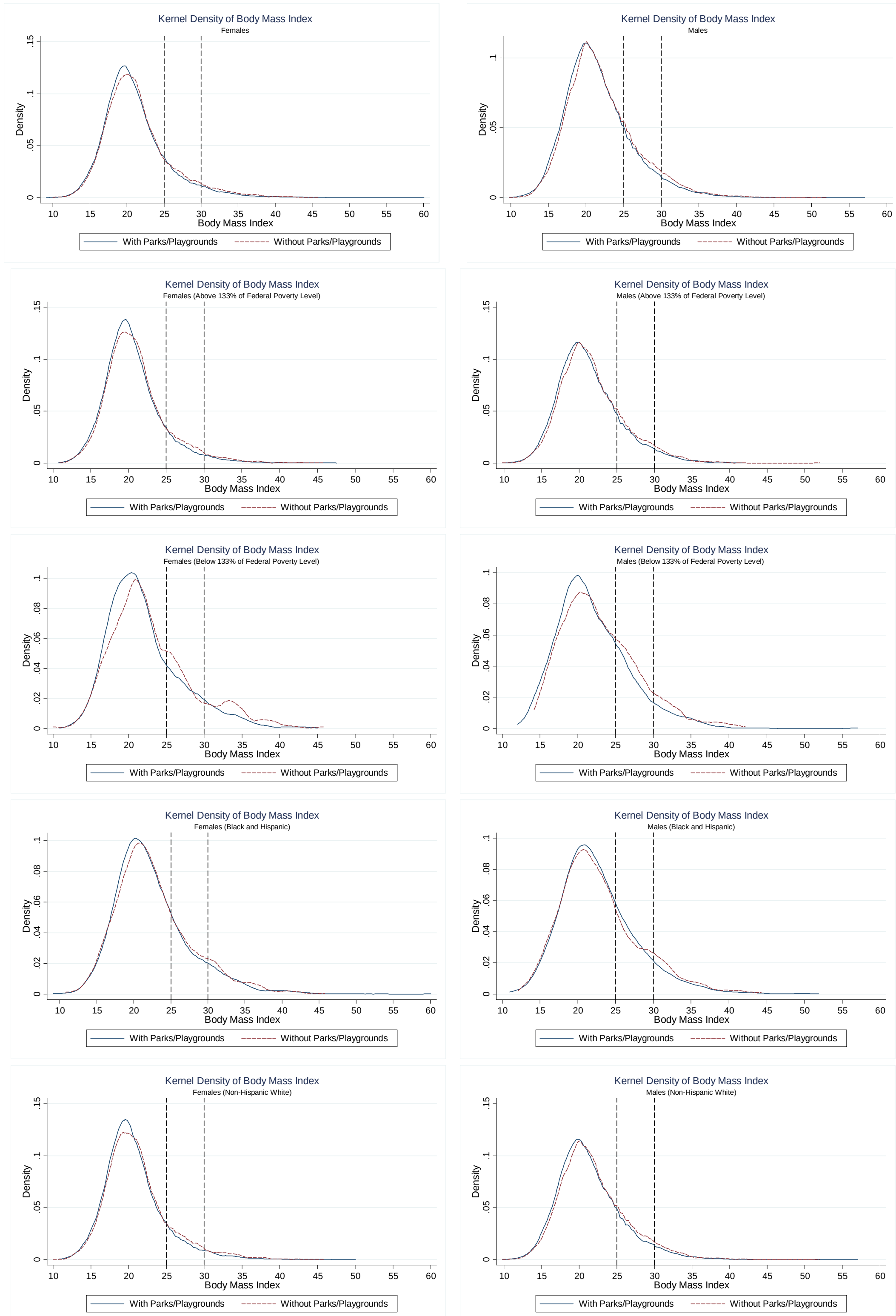
	Matched	-0.01	0.16	-0.01	0.14
No. of kids in the household	Unmatched	NA	NA	-0.05***	0.00
	Matched	NA	NA	0.06***	0.00
Household income below the poverty line (yes/no)	Unmatched	0.01***	0.00	0.01***	0.00
	Matched	0.01	0.09	0.01	0.18
Household income in 100-200% of the poverty line (yes/no)	Unmatched	0.01	0.15	0.01*	0.03
	Matched	0.01	0.15	0.01	0.10
Household income in 200-300% of the poverty line (yes/no)	Unmatched	0.00	0.77	0.01	0.22
	Matched	0.01	0.21	0.01	0.46
Perceived neighborhood characteristics					
Neighborhood sidewalks and pathways (yes/no)	Unmatched	-0.52***	0.00	-0.54***	0.00
	Matched	-0.13***	0.00	-0.11***	0.00
Community center/kids' club (yes/no)	Unmatched	-0.30***	0.00	-0.31***	0.00
	Matched	-0.08***	0.00	-0.06***	0.00
Help each other in the neighborhood (1=absolutely no to 4=absolutely yes)	Unmatched	-0.02	0.11	-0.05***	0.00
	Matched	-0.06***	0.00	-0.08***	0.00
Feeling safe in the neighborhood (from 1=never to 4=always)	Unmatched	0.07***	0.00	0.05***	0.00
	Matched	-0.03*	0.02	-0.04***	0.00

Asterisks, ***, **, and *, indicate the statistical significant level at zero, one, and five percent.

[a]. Mean differences of each matching covariate between those in the comparison group and those in the treated group. All tests are based on Covariate Matching with 1 neighbor. Results from matching with 5 neighbors are similar. T-statistics are calculated as

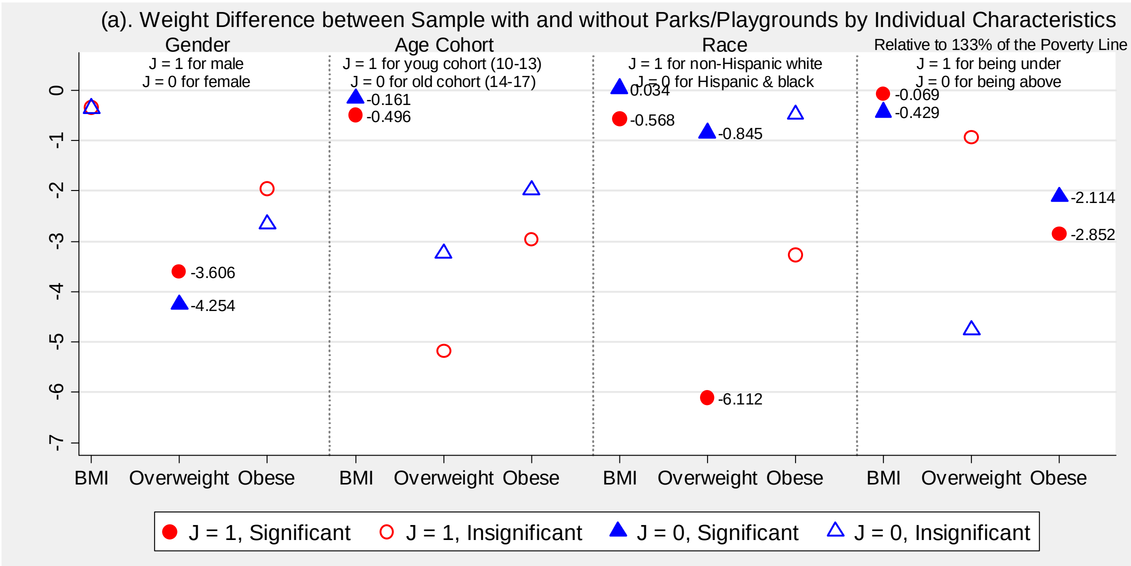
$$t_{\left(\overline{X}_{Treated} - \overline{X}_{Control}\right)} = \frac{\overline{X}_{Treated} - \overline{X}_{Comparison}}{\sqrt{\frac{\sigma^2_{Treated}}{n_1} + \frac{\sigma^2_{Comparison}}{n_2}}}$$

where n_1 and n_2 are the number of observations for the treatment and comparison groups on the support, respectively.



(a) Female (b) Male

Figure 1: BMI Distributions of Children with and without A Park/Playground in Their Neighborhood (Full Sample and Different Subsamples Based on Individual Characteristics)



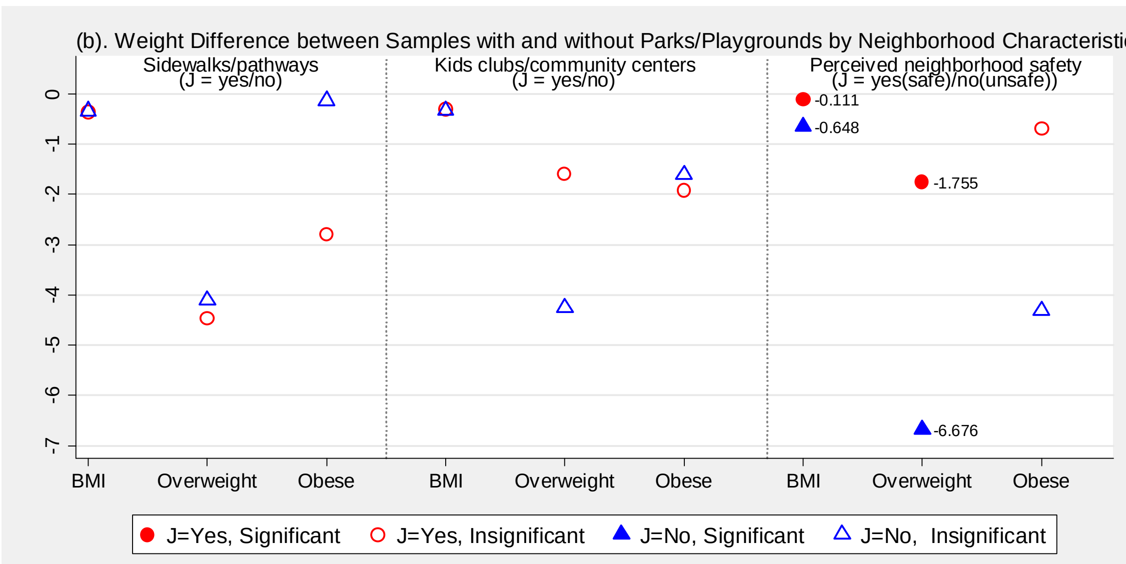


Figure 2. Mean difference of weight measure between samples with and without parks/playgrounds by characteristics of individuals and their neighborhoods

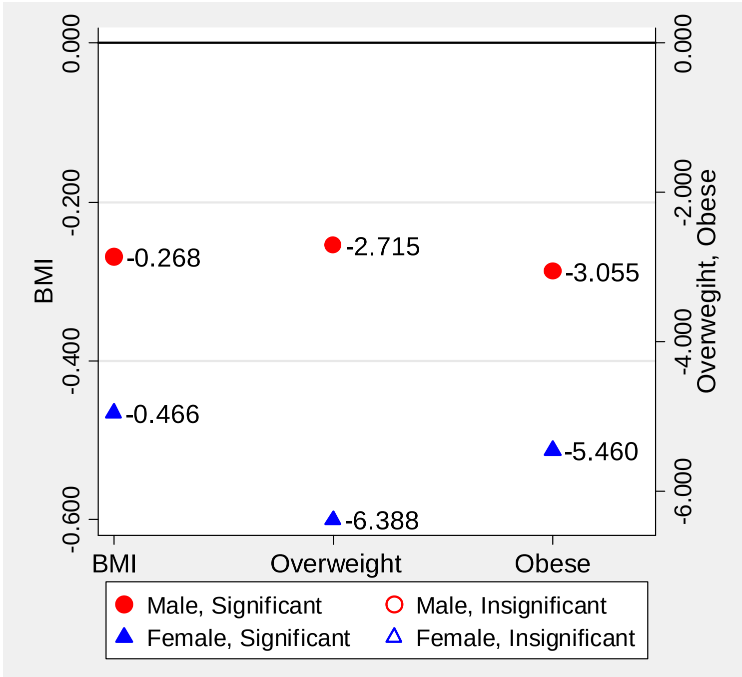


Figure 3. Overall treatment effects of neighborhood parks/playgrounds on weight status for the control group

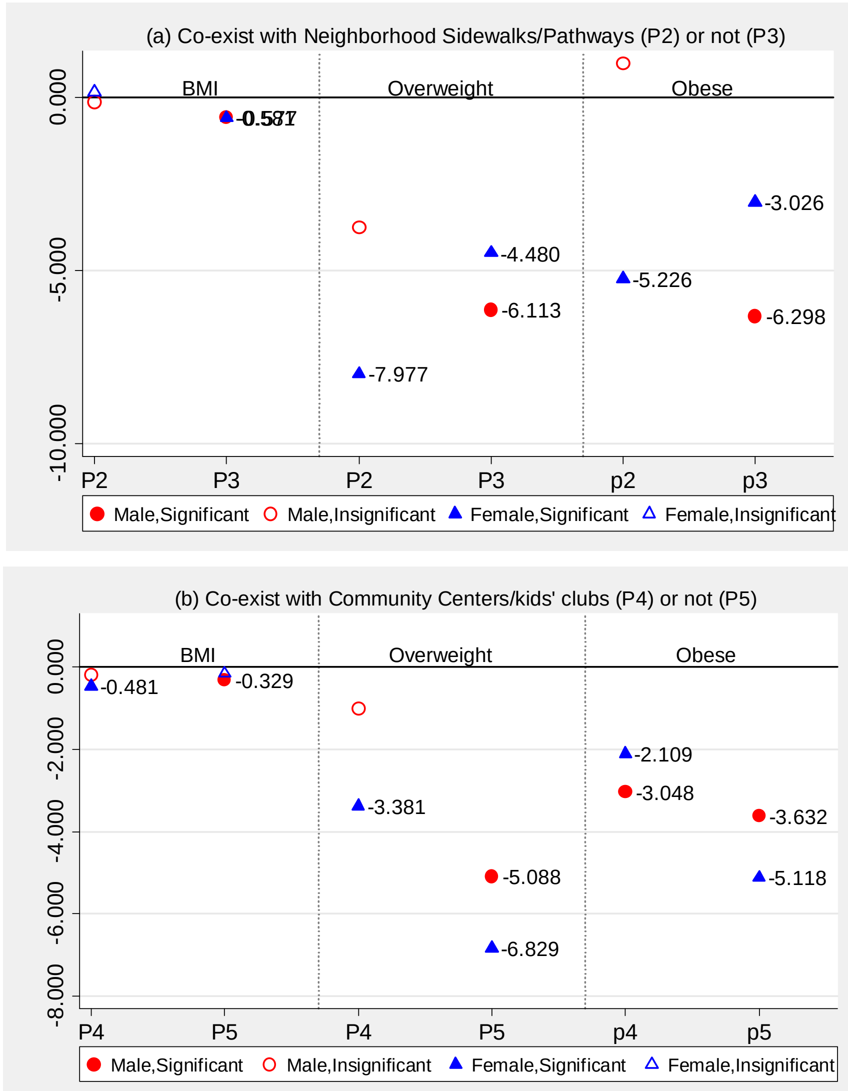


Figure 4. Treatment effects of neighborhood parks/playgrounds on weight status condition on other amenities

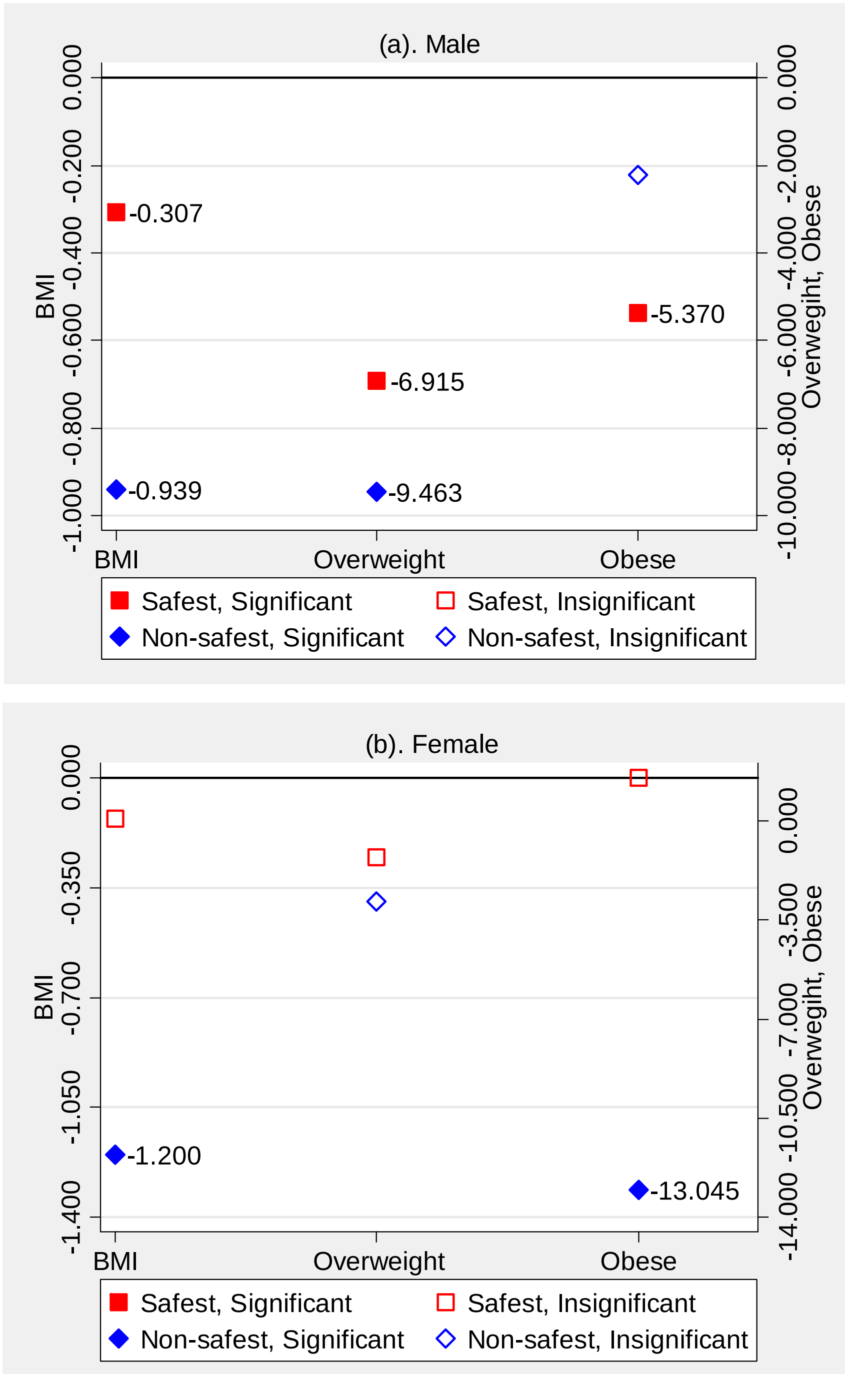


Figure 5. Matching results on weight status among subgroups with different level of perceive neighborhood safety

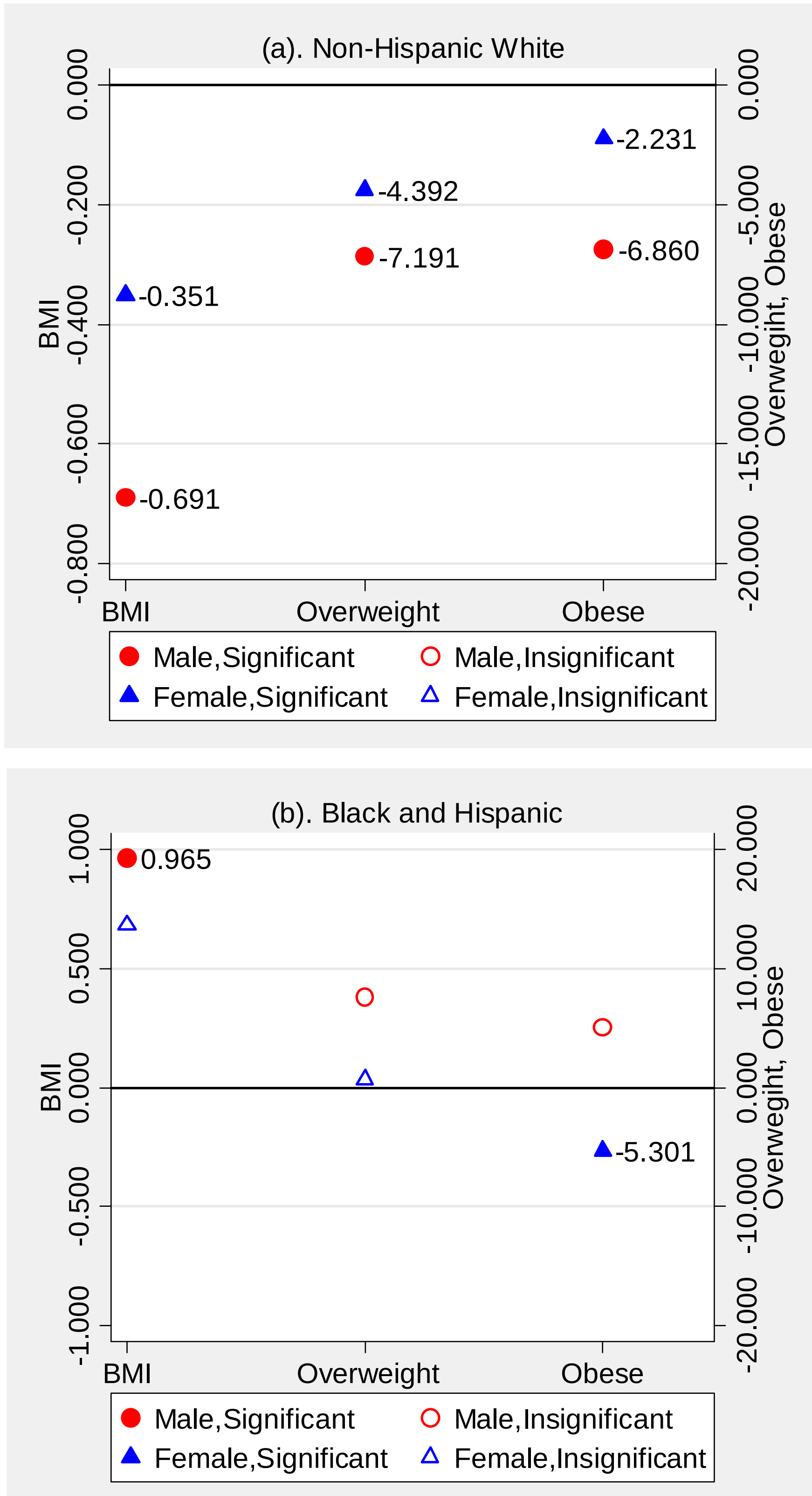


Figure 6. Matching results on weight status among different racial subgroups

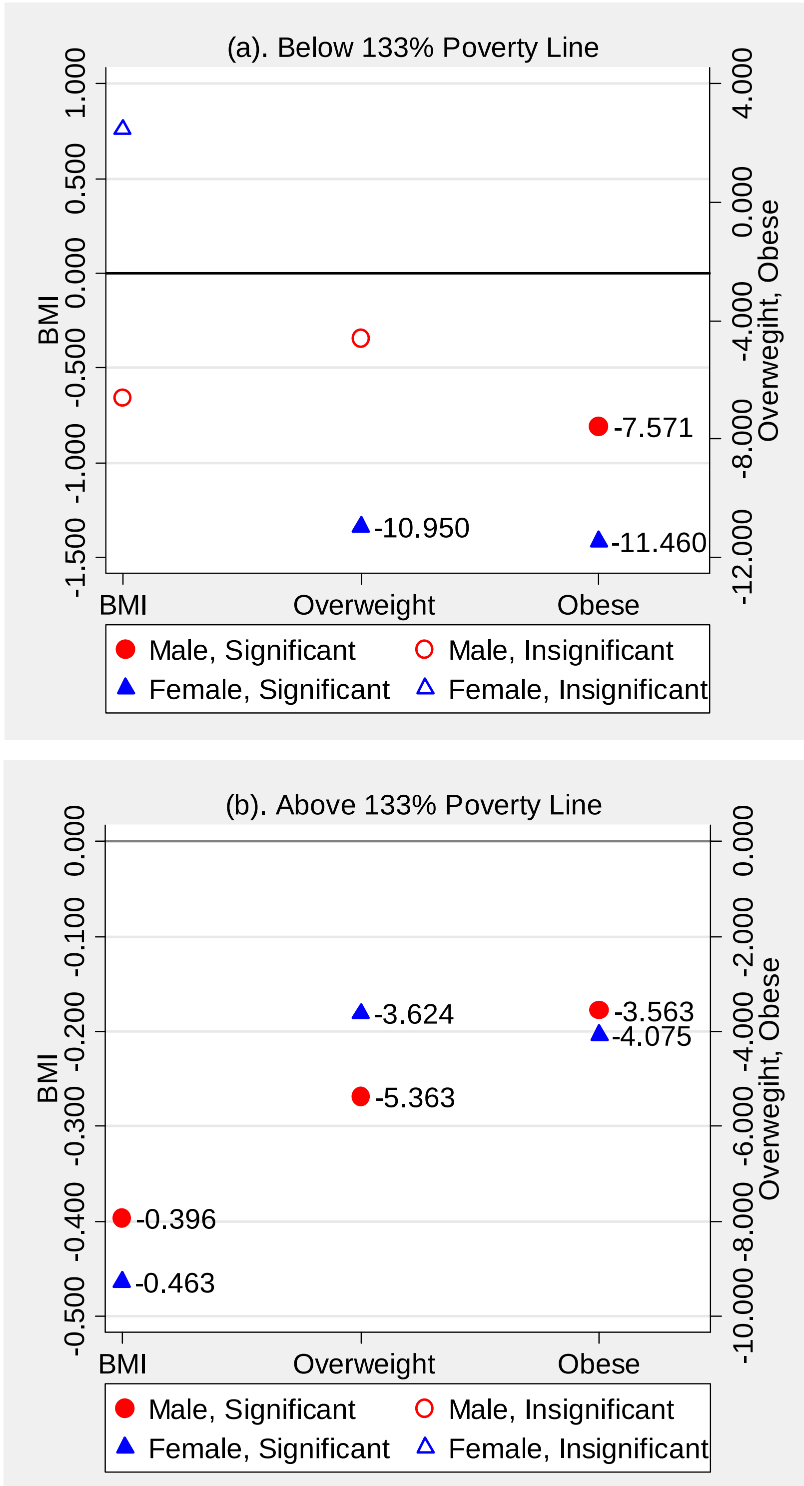


Figure 7. Matching results on weight status among samples living above or below 133% of the Federal poverty line

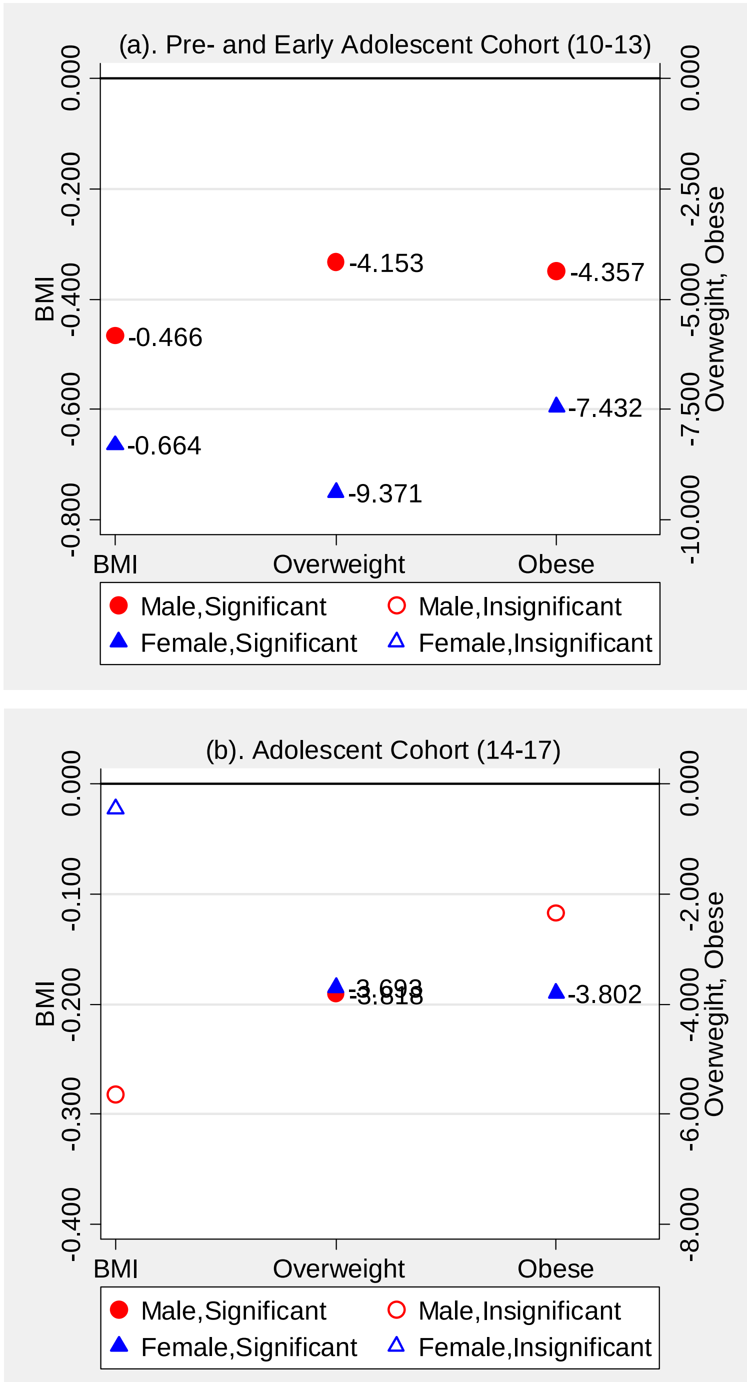


Figure 8. Matching results on weight status by age cohorts

[1] See Abadie and Imbens (2011) for detailed discussion of covariate matching techniques.

[2] We use the diagonal matrix, of which the diagonal elements are the inverses of the variances of X_i (the element of the set of covariates), as our weighting matrix V. The weighting matrix V accounts for the difference in the scale of the covariates.

[3] The growth chart can be found at the CDC website: http://www.cdc.gov/growthcharts/.

[4] To save space we do not present those histogram graphs, but they are available upon the request.

[5] For the other matching models discussed in the rest of this paper, we do not present the balancing test for the matching variables due to the limited space, but they are available upon request.

[6] Let's take obesity among males as an example. The obesity rate among the comparison group is 19.23 percent. The treatment effect is 3 percentage points. Therefore, the percentage change equals 100%*3/19.23=23%.