CHILDHOOD OBEISTY AND ACADMIC ACHIEVEMENT

by

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Dedicated to my parents Jianguo and Pengyin

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Abstract

Childhood obesity has become a public health crisis in the United States. My dissertation aims to advance our understanding of the relationships between obesity and school performance. In particular, it addresses the following three key questions: (1) Does obesity lead to poor school performance? (2) What are the potential pathways underpinning the obesity penalty in academic achievement? (3) Who are at greatest risk to experience the obesity penalty?

In the first paper, I examine the causal effect of childhood obesity on academic achievement. My work employs propensity score matching to minimize biases related to omitted variables, and sensitivity analysis to evaluate the robustness of estimates against biases related to unobserved variables. In the second paper, I use a decomposition method to assess the causal pathways that produce obesity penalties in academic achievement. In the third chapter, I consider the differential effects of obesity across the distribution of test scores via a quantile regression approach. I find that obese eighth graders, on average, score 0.17 standard deviations (SD) lower in reading and 0.16 SD lower in math than their normal-weight counterparts—a magnitude roughly one-sixth of the black-white achievement gap. These estimates are robust, unless an unobserved variable increases the odds of becoming obese by more than twenty percent. Further, poor work habits and reduced educational expectations account for nearly half of the obesity penalty, while the roles of behavioral problems and physical health are minimal. Finally, low-achieving students are disproportionately affected by obesity.

In an era of growing obesity prevalence and of continuous decrease in the timing of onset of obesity, my dissertation uncovers substantial losses in cognitive development that occur as a direct consequence of childhood obesity at younger ages. It provides new evidence that some early health conditions can contribute non-trivially to educational inequality. It reveals the potential benefits for academic achievement that policies designed to curb childhood obesity could have.

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Introduction

Research questions

A growing number of studies have demonstrated that early health is an important mechanism producing social inequality. Of the multiple early health conditions that children may experience, childhood obesity is a strategic one both because of the sheer variety of effects associated with it and because of its rapidly ascending prevalence. The rates of obesity among students age 12-19 have tripled over the past four decades. It is estimated that in 2006, one in five school-aged children are obese. With so many students enter into school carrying the health burden, it is natural to study how these health problems affect their school performance and wellbeing. Yet despite its centrality it has received less attention that it deserves in the literature in sociology of education and sociology in general. Past studies have not established the causal effect and potential pathways. Further, it remains unclear whether the obesity effect is equal for everyone.

This dissertation aims to advance our understanding of the relationships between obesity and school performance during childhood. In particular, it addresses the following three key questions: (1) Does obesity lead to poor school performance? (2) What are the potential pathways underpinning the obesity penalty in academic achievement? (3) Who are at greatest risk to experience the obesity penalty? Answering these three questions will contribute to our understanding of the role of early health in stratification processes.

What past studies have found?

Although past studies have consistently shown that obesity is associated with lower levels of cognitive function (Li et al. 2008; Miller et al. 2006; Shore et al. 2008), scholars disagree about the causal impact of obesity on standardized test scores, and associated gender differences in the impacts (Averett and Stifel 2010; Datar, Sturm and Magnabosco 2004; Kaestner and Grossman 2009). For instance, several earlier studies reported a negative effect of obesity on standardized test scores and grade point averages, using ordinary least squares (OLS) regression with cross-sectional data (Datar and Sturm 2006; Judge and Jahns 2007; Shore et al. 2008). Averett and Stifel (2010) have found the subtle racial and gender differences in obesity penalties with the instrumental variable approach. Using sample of children from the National Longitudinal Study of Youth 1979, they showed that white boys scored approximately one standard deviation lower in reading than their normal-weight counterparts. But Kaestner and Grossman (2008) reported no negative effect of obesity on test scores using the instrumental approach and the same data. In summary, there is no consensus on the causal effect of childhood obesity on academic achievement.

In the study of potential pathways linking obesity and poor academic achievement, past studies have only focused on behavioral problems and school absence, but ignored reduced educational expectation and work habits. Further, the degree of mediation has varied across studies that examine the mediating roles of self-esteem and school absence. For instance, Tershakovec and colleagues (1994) reported that, among urban African American elementary school students, the negative effect of obesity on school performance vanished after controlling for self-esteem (Tershakovec, Weller and Gallagher 1994), but Crosnoe (2007) found that one-third of the lower odds of college enrollment among obese girls was attributable to measures of externalizing behavioral problems (alcohol and marihuana use), school disengagement (class failures and unexcused school absences), and suicidal ideation (Crosnoe 2007). Thus, there is no conclusive evidence of the role of low self-esteem and behavioral problems as mediators. Additionally, a study of Arkansas elementary and middle school students showed that controlling for weight-based teasing slightly mediated the negative impact of obesity on test scores (Krukowski et al. 2009). Therefore, past studies have reported inconsistent findings about the relative importance of each pathway.

Few studies have assessed the heterogeneous effects of obesity on school performance. Only one study has addressed the differential effects of obesity by test scores (Eide, Showalter and Goldhaber 2010). Using a quantile regression approach, Eide and colleagues (2010) found that being overweight (BMI >90^{th} percentile) was correlated with *higher* reading scores among low-achieving students, but *lower* reading scores among high-achieving students for children in the second-wave of the Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID).

Problems faced by past studies

Empirical investigations of childhood obesity and academic achievement have faced many problems. I highlight major challenges in investigating the causal effects, underlying pathways and differential effects in this section.

In the study of causal effect of childhood obesity on academic achievement, scholars often face the challenge that any observed obesity gaps may be due to preexisting differences rather than a casual relationship. For instance, children who gain excessive weight may come from more disadvantaged families (i.e. biases due to observed variables) or possess other unobserved characteristics that lead to worse outcomes, such as lack of concentration (i.e. biases due to unmeasured variables). Past estimation approaches are insufficient to tackle these challenges. First, the ordinary least square approach, using contemporaneous measures of obesity and test scores, not only is impossible to establish the temporal order of obesity and educational outcomes, but also suffers from omitted-variable bias. For example, the estimates in the work of Datar and Sturm (2006) and Judge and Johns (2007)were likely biased because the models lacked measures of nutrition, neighborhood, and school characteristics, which may affect both obesity and educational outcomes (Jyoti, Frongillo and Jones 2005). Second, the instrumental variable approach may not correctly estimate the causal effect of obesity on test score, if the validity of the instruments is questionable. For instance, the use of either maternal weight (Averett and Stifle 2010) or children's prior weight (Kaestner and Grossman 2009) as instrumental variables may violate the exclusion restriction, because these variables can affect school performance through characteristics other than obesity, such as birth weight. Third, past studies do not adequately assess the robustness of their estimates in the face of bias related to unmeasured variables. In short, these problems suggest that past studies are insufficient to establish a causal link between obesity and academic achievement.

Although the first chapter suggests a causal link between childhood obesity and poor school performance, it remains unclear how exactly childhood obesity affects school performance. Without a comprehensive framework, past studies have ignored two important pathways- low educational expectations and poor work habits. Further, although several studies have examined the mediating effects of behavioral problems and school absence, they have reported inconsistent findings about the relative importance of each pathway. Third, past studies do not perform decomposition analysis to uncover the source of obesity gaps. These insufficiencies have created difficulty to design effective policy intervention that curb the deleterious effects of obesity. In short, it is necessary to comprehensively assess the relative contributions of four pathways to the overall obesity penalties in test scores.

In the study of differentiating effects of obesity on academic achievement, past study face the problems of reverse causality and omitted variable biases. Eide and colleagues (2010) employed a cross-sectional design that was impossible to establish the temporal order of being obese and poor test scores. They also do not measure students' physical activity level that may determine excessive weight and poor scores. Second, the authors did not investigate whether the underlying pathways are the same for all students. Third, using a broad sample of children and adolescents (ages 5 through 18) likely introduced additional selection bias, because early drop-outs can lead a sample with only students maintaining satisfactory academic progress.

My approach to solve problems

My dissertation research has adopted the following research design to offer new perspective and provide robust estimates.

In the first chapter, I identify the causal effect of childhood obesity on academic achievement with propensity score matching and sensitivity analysis. To reduce biases related to observed variables, I use propensity score matching to compare the test scores between obese students and their thinner counterparts. I adopt three strategies to ensure the validity of matching estimates: a clear definition of the treatment and control groups, controls for comprehensive covariates, and the adoption of various matching regimes (Morgan and Harding 2006). In particular, I have control for nutritional intake, exercise level, and neighborhood features that are not available in past studies. Matching can yield unbiased estimates of the obesity penalty only if unmeasured variables do not correlate with children's propensity to be obese or with test scores. To assess the robustness of the matching estimates in the face of bias related to unobserved variables, I adopted three methods, including regression adjustment of the matched data (Abadie et al. 2001), adding a pre-treatment outcome

(Smith and Todd 2005), and conducting Rosenbaum bound sensitivity analysis (DiPrete and Gangl 2004). In particular, the Rosenbaum bound sensitivity analysis enables me to evaluate how influential an unmeasured variable should be to challenge the validity of the matching estimates. The analysis begins with a specification of the correlation between an unmeasured confounding variable and a student's propensity of being obese as gamma (Γ), expressed as log odds. A subsequent step is identifying a cutoff point of Γ where the matching estimates statistically insignificant. Third, I take advantage of the longitudinal nature of data to ensure that obesity occurs before test scores. This can minimize potential reverse causality.

In the second chapter, to comprehensively assess the underlying pathways linking obesity and school performance, I incorporate the non-cognitive skill formation perspective into the empirical investigation. I hypothesize that poor work habits, behavioral problems, reduced educational expectations, and school absence collectively explain the obesity penalty, but poor work habits are the most important one. Because work habits are the implementation of expectations, focus on attention level and quality of school attendance, and directly relate to learning process. To evaluate the relative importance of each pathway and uncover the sources of obesity gaps, I apply a regression-based decomposition method. This method has two steps. First, I use regression analysis to examine how obesity effects are explained by each pathway. An examination of changing regression coefficients will demonstrate the relative importance of each mechanism linking obesity and poor test scores. Recognizing that the observed obesity gaps in test scores can be due to differences in the distributions of covariates and differences in effect sizes between obese students and their normal-weight counterparts, I apply the blinder-Oaxaca decomposition to show that the obesity effects are attributable to differences in population means, effect sizes and interactions for each pathway. Here, I am cautious to make causal inference because there are potential unmeasured variable can determine both obesity and underachievement.

In the third chapter, I employ a quantile regression approach to uncover the heterogeneous effects of childhood obesity on academic achievement across students' ability. The quantile regression is better than the ordinary least square regression to address this question in two ways. First, it can show the obesity effect at particular points of the test scores distribution, and provide simultaneous tests whether he obesity effects are equal for everyone. Second, it is insensitive to outliers. In this study, I extend the current research by further reducing biases related to nutrition, physical activity and neighborhood characteristics, and investigating the potential group-specific pathways. However, I am cautious to make causal inference. There is a possibility that unmeasured variable can determine both obesity and poor test scores at particular percentile of the distribution.

Summary of main findings

Using data from the Early Childhood Longitudinal Study-Kindergarten cohort (ECLS-K), my dissertation has provided new evidence that early health conditions have significantly reduced academic achievement.

First, I find that obese eighth graders have an average loss of 0.17 standard deviations in reading and 0.16 standard deviations in math, roughly one-sixth of the Black-White achievement gap. The obesity penalties for girls are larger than for boys in both subjects. Sensitivity analyses reveal that these results are robust, unless an unobserved variable related to academic achievement increases the odds of becoming obese by more than twenty percent. This is equivalent to the effect of increasing a newborn's birth weight by twelve ounces. The estimated obesity effects are reliable. They are insensitive to matching methods, alternative definition of weight, sub group analysis and adjustment of missing values. Overall, these findings provide compelling evidence on a true causal link between childhood obesity and poor school performance.

Further, I find that poor work habits and low educational expectations account for nearly half of the obesity penalty in reading and two-fifth of the obesity penalty in math, while the role of behavioral problems and physical health are unimportant. Decomposition results further demonstrate that the majority of the observed differences are due to differences in the prevalence of poor work habits and reduced educational expectations between obese children and their thinner peers. This chapter is the first to empirically test the role of work habits in explaining the obesity penalty and, more importantly, confirms the role of non-cognitive skills in boosting cognitive skills during childhood.

Finally, I find heterogeneous effects of obesity on test scores across students' ability level. For instance, the obesity gaps in reading are largest among students in the 0.1 quantile distribution; the gaps for this group are about 20 times larger than those for students at the 0.9 quantile. Further, these varying effects of obesity are attributed to different mediating factors. Among low-achieving students, poor work habits account for the majority of the score gaps in reading. For median students, persistent weight stigma, measured by reduced parental educational expectations and behavioral problems, is the most important factor explaining reading test score gaps associated with obesity.

Contributions to the field

In an era of growing obesity prevalence and of continuous decrease in the timing of obesity, my dissertation uncovers substantial losses in cognitive development that occur as a direct consequence of childhood obesity at younger ages. It provides new evidence that some early health conditions can contribute non-trivially to educational inequality. It reveals the potential benefit for academic achievement that policies designed to curb childhood obesity could have. This is the first paper to apply propensity score matching to evaluate the causal effect of obesity on test scores, and directly assess the degree of bias associated with unmeasured variables, and clarify conditions under which the obesity effects remain valid.

The section on evaluation of pathways contributes to the ongoing debate about early health and adult individual trajectory of status attainment and has important implications for polices designed to attenuate childhood obesity. I demonstrate that fostering good work habits is essential to improve the academic performance of obese students and, more importantly we show convincingly that effective policy interventions should target specific groups, particularly those who rank lowest in measures of academic achievement. Finally the dissertation contributes to an agenda for future research on the ultimate consequences of child obesity on adult labor market performance and on aggregate income inequality. Early onset of obesity negatively affects cognitive development and if cognitive development is tightly connected to adult earnings capacity, what will be the end results of current trends toward increased child obesity.

Chapter I Does Obesity Lead to Poor School Performance? Estimates from Propensity Score Matching

Abstract

High body weight is negatively associated with test scores among elementary and middle school students. Are these negative outcomes due to preexisting differences, or are they a casual effect of childhood obesity? To better understand the causal mechanisms underlying this pattern, I use a propensity score matching approach to control for biases from observable preexisting differences, and conduct sensitivity analysis to assess the impact of biases from unobserved variables. Using data from the Early Childhood Longitudinal Study, the matching models reveal that obese eighth graders, on average, score 0.17 standard deviations lower in reading and 0.16 standard deviations lower in math, a reduction roughly equivalent to one sixth of the racial achievement gap. Obesity penalties are larger for girls than for boys in both subjects. Differences between obese and normal-weight children decline slightly after adjusting for missing values. Findings from sensitivity analyses indicate that unmeasured variables would need to increase the odds of becoming obese by at least 20 percent to change the conclusion.

Key words: obesity, academic achievement, propensity score matching

Introduction

Childhood obesity has become a public health crisis in the United States. The rates of obesity among children and adolescents have tripled over the past four decades(Wang and Beydoun 2007). Roughly one in five children and adolescence ages 2 through 19 was obese (Ogden et al. 2010). Treatments for obesity-related conditions in the United States cost roughly $150 billion per year (Cawley 2010). Past research has revealed substantial negative impacts of obesity on public health and the health care system (Finkelstein, Ruhm and Kosa 2005).

Few studies, however, have examined the causal effect of childhood obesity on academic achievement. Although past studies have consistently shown that obesity is associated with lower levels of cognitive function (Li et al. 2008; Miller et al. 2006; Shore et al. 2008), scholars disagree about the impact of obesity on standardized test scores, and associated gender differences in the impacts (Averett and Stifel 2010; Datar, Sturm and Magnabosco 2004; Kaestner and Grossman 2009). Further, the methods employed in previous studies are insufficient to establish a causal effect of obesity on academic achievement—any observed negative effect may be due to preexisting differences rather than a casual relationship. Children who gain excessive weight may come from more disadvantaged families or possess other unobserved characteristics that lead to worse outcomes. For instance, the ability to concentrate may be an unobserved characteristic that affects both weight and school performance;

drawing conclusions about the causal relationship between obesity and poor test scores is difficult because of the potential for unobserved characteristics.

To identify the casual effect of childhood obesity on academic achievement, I employ propensity score matching to reduce preexisting differences associated with observed variables. I use a sensitivity analysis to evaluate the strength of the matching estimates against the bias associated with unobserved variables. To alleviate the possibility of reverse causality, I also use predictor variables measured in fifth grade to predict outcomes in eighth grade. Using data from the Early Childhood Longitudinal Study, the matching models reveal that obese eighth graders score, on average, 0.17 standard deviations lower in reading and 0.16 standard deviations lower in math, a reduction roughly equivalent to one sixth of the racial achievement gap. These estimates are robust unless an unmeasured variable would have to increase the odds of becoming obese by at least 20 percent to change the conclusion. Obesity penalties are larger for girls than for boys in both subjects.

This paper makes three important contributions. First, this is the first study to apply propensity score matching to investigate the causal effect of childhood obesity on academic achievement. Second, the analyses include important controls for determinants of obesity (i.e., nutrition and exercise) that have not been used in past studies. Third, this is the first paper to use formal sensitivity analysis in the study of obesity and school performance to evaluate the robustness of matching estimates in the face of selection bias.

Potential causal pathways

Theoretical perspectives focus on four characteristics through which childhood obesity may be associated with poor school performance: behavioral problems, reduced educational expectation, poor work habits and school absence. First, obese individuals have lower levels of self-esteem, and exhibit more behavioral problems that disturb their cognitive development (Falkner et al. 2001; Miller and Downey 1999; Strauss 2000). Second, obese individuals and their parents have lower educational expectations and lower levels of subsequent parental investment (Ball, Crawford and Kenardy 2004; Crandall 1991; Crandall 1995). Third, obese students may also lack attention, concentration, task persistence, and flexibility that are key to effective learning (Rimm and Rimm 2004). Research has firmly established that behavioral problems, reduced levels of educational expectations and poor work habits have a detrimental impact on academic achievement (Bub, McCartney and Willett 2007; Campbell et al. 2006; Fan and Chen 2001; Farkas 2003; McLeod and Kaiser 2004). Thus, if the prevalence of these three factors is higher among obese individuals, it may lead obese children to score poorly on standardized tests.

Fourth, frequent school absences among obese students, due to obesity-related health problems, may hinder the learning process. Obesity is often associated with chronic physical health problems including sleep apnea, asthma, and cardiovascular disease (Daniels 2006). These chronic health problems can lead to fatigue, difficulty concentrating in class, and frequent school absences due to treatment or discomfort (Currie 2009). While obesity is associated with frequent school absences (Geier et al. 2007; Schwimmer, Burwinkle and Varni 2003), chronic health problems can curb school attendance by an average of two more days per year (Bonilla et al. 2005). Thus, if the prevalence of chronic health problems is higher among obese children, and school attendance is crucial to academic succeess (Perez-Chada et al. 2007), obese students, with frequenct school absences, may do poorly in school.

Obesity may affect girls' academic achievement more than boys' achievement. First, heavy girls are more aware of their weight because girls mature earlier than boys (Rimm and Rimm 2004). Second, the degree of stigmatization (such as teasing, and verbal and physical bullying) is higher among obese girls than obese boys (Fikkan and Rothblum 2011; Tang-Peronard and Heitmann 2008). Third, reactions to weight bias are more problematic among girls than boys. A number of studies have consistently found a larger negative impact of obesity on self-esteem for women than men (Miller et al. 2006). Finally, lower educational expectations are more prevalent among girls than among boys. In sum, a stronger degree of stigma and consequently more severe problems suggest a larger obesity penalty in academic achievement for girls than boys.

Despite these initial observations, a few arguments suggest that obesity may be a marker rather than a causal factor. First, any observed negative effect may be due to preexisting differences rather than a casual relationship between childhood obesity and poor school performance. Children who gain excessive weight may come from more disadvantaged families, have poor nutrition, or possess other unobserved characteristics that lead to worse outcomes. For instance, Datar and colleagues (2004) found that obesity differences in first-grade reading scores become insignificant after including socioeconomic and behavioral variables. Similarly, poor nutrition among obese children may diminish their ability to think and concentrate. Children who consume high-sugar drinks may often feel tired because eating sweets leads to a drop in blood sugar. Those who skip meals may not have enough energy for learning (Rimm and Rimm 2004). Further, obese children may have unobserved characteristics, such as a low IQ, that are counterproductive to learning. Additionally, lower test scores may cause excessive weight gain. For some children, poor school performance can be a stressor, causing them to seek comfort from highly caloric foods. Given these considerations, obesity may not have a causal effect on school performance.

Previous empirical research

Empirical studies of adolescents have consistently found obesity penalties in school performance and educational attainment, and have revealed larger obesity effects among female students than among male students (Crosnoe 2007; Sabia 2007). In contrast, empirical investigations of younger students have had mixed results, depending on the measures of cognitive development, methods, and age.

Several earlier studies reported a negative effect of obesity on standardized test scores and grade point averages, using ordinary least squares (OLS) regression with cross-sectional data (Datar and Sturm 2006; Judge and Jahns 2007; Shore et al. 2008). However, an OLS approach using contemporaneous measures of obesity and test scores has two limitations when making causal inferences: not only it is impossible to establish the temporal order of obesity and educational outcomes, these analyses also suffer from omitted-variable bias. For example, OLS estimates in the work of Datar and Sturm (2006) and Judge and Johns (2007)were likely biased because the models lacked measures of nutrition, neighborhood, and school characteristics, which may affect both obesity and educational outcomes (Jyoti, Frongillo and Jones 2005). Biases also arise when unmeasured variables, such as intelligence and genetic factors, simultaneously determine both obesity and test scores (Cawley 2004). OLS regressions that control for prior weight (Crosnoe 2007; Datar, Sturm and Magnabosco 2004) alleviate reverse causality to some extent, but remain vulnerable to omitted variable bias.

To control for unobserved genetic factors that may affect both obesity and test scores, some scholars have adopted an instrumental variable approach (Averett and Stifel 2010; Ding et al. 2009; Kaestner and Grossman 2009; Sabia 2007). Kaestner and Grossman (2008) reported no negative effect of obesity on test scores; however, using the same sample of children from the National Longitudinal Study of Youth 1979, Averett and Stifel (2010) identified subtle racial and gender differences in obesity penalties. For instance, Averett and Stifel (2010) found that obese white boys scored approximately one standard deviation lower in reading than their normal-weight counterparts. Three limitations might undermine this causal conclusion. First, the use of either maternal weight or children's prior weight as variables may violate the exclusion restriction, because these variables can affect school performance through characteristics other than obesity, such as birth weight. One recent study found that controlling for actual obesity-related genetic factors removes the negative impact of obesity on the probability of employment among respondents in their mid-twenties (Norton and Han 2008). Second, neither study controlled for nutrition intake or exercise levels, which are crucial determinants of childhood obesity. Third, these studies did not use formal sensitivity analyses to assess the robustness of the instrument variable estimates in the face of selection bias.

Finally, Morris (2007) combined propensity score matching and the instrumental variable approach to examine the obesity gap in adult employment. Use of propensity score matching reduces the biases associated with observed preexisting differences between obese and non-obese individuals; however Morris examined employment rather than educational outcomes, and did not use formal sensitivity analysis to test the robustness of the matching estimates. In short, prior empirical studies are insufficient to establish the causal effects of childhood obesity on academic achievement.

In this study I extend previous investigations by applying propensity score matching and sensitivity analysis to the study of educational outcomes. To establish causal order and alleviate the possibility of reverse causality, I use predictors from fifth grade (or earlier) and outcomes measured in eighth grade. To reduce omitted variable bias, I control for nutritional intake, exercise level, and neighborhood features. The use of propensity score matching also mitigates bias from observed preexisting differences between obese students and their normal-weight counterparts. I conduct Rosenbaum bound sensitivity analysis to evaluate the strength of matching estimates in the face of selection bias.

Research hypotheses

In this study I investigate the causal effect of childhood obesity on standardized test scores, and explore associated gender differences. Based on the weight stigma and physical health perspectives, I expect that obesity will have a negative impact on reading scores, and math scores. I further expect that due to gender differentials in the degree of stigma and responses to stigma, obesity penalties in academic achievement will be larger among girls than among boys.

Methodology

Data

I use the kindergarten, fifth-grade, and eighth-grade public-use data from the Early Childhood Longitudinal Study (ECLS-K) for the analysis. The Department of Education sampled 19,000 children enrolled in kindergarten in the fall of 1998, and followed them through eighth grade. The main purpose of the data collection was to track students' academic trajectories. The survey included seven waves of data collection: fall of kindergarten (1998), spring of kindergarten (1999), fall of first grade (1999), spring of first grade (2000), spring of third grade (2002), spring of fifth grade (2004) and spring of eighth grade (2006). The ECLS-K had a multiple-stage sample design, drawing respondents from students within schools located in the primary sampling units.[1]

The ECLS-K kindergarten, fifth-grade, and eighth-grade data is suitable for two reasons. First, the data include complete measures of nutrition, physical activity, family socioeconomic background, neighborhood safety, and school characteristics. Specifically, student-reported nutrition measures are only available for fifth grade. Relatively comprehensive measures not only reduce the likelihood of omitted-variable bias, but also ensure the validity of matching estimates by improving matching quality. Second, estimates based on data from the eighth graders (14-15 years old) can be compared to studies using other datasets in the United States, such as The National Longitudinal Study of Adolescent Health (Add Health), the National Longitudinal Survey of Youth (NLSY) and the Panel Study of Income Dynamics (PSID). Despite these advantages, the ECLS-K lacks measures of intelligence, maternal weight, genetic factors, and time-use information, all of which may affect both obesity and test scores. Although a matching approach cannot directly control

[1] Detailed information can be found at http://nces.ed.gov/ecls/kindergarten.asp.

these unmeasured factors, the sensitivity analysis can reveal the effect of these unmeasured variables on the robustness of the matching estimates.

Sample

The analytic sample consists of 4,460 white children whose height and weight are measured at fifth grade and eighth grade.[2] To gauge the enduring effect of obesity, I excluded the 33 obese children who lose weight (i.e. whose BMI drop below the 95^{th} percentile), and the 24 children who gain weight (i.e. whose BMI move above the 95^{th} percentile) between fifth and eighth grade[3]. Nearly 23 percent of these children are classified as obese, with a BMI at or above the 95^{th} percentile in both fifth and eighth grade. The case-complete sample includes 2,631 white children. I used the final sample of 2,631 children with complete data on all covariates in the primary analysis, and supplemented the primary results with an analysis of the imputed sample.

Examining the patterns among the missing covariates revealed that 12 of 20 covariates had missing values for at least some students, and the rate of missing values for four variables (reading scores in kindergarten, math scores in kindergarten, father's occupational status, and free lunch recipient status) account for the majority (approximately 75 percent) of missing data. Assuming the observations are missing

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[2] I limit the analytic sample to white children because there are not enough African American and Hispanic children to allow effective matching.

[3] As the ECLS-K recorded students' height and weight at fifth grade and eighth grade, the precise time of weight change is unknown within a three-year span. Thus, it is hard to group them into the treatment group (i.e. obesity) or the control group (i.e. normal weight). Further, additional sensitivity analysis that includes these 57 children yields similar results as those analyses excluding them. Therefore, this exclusion does not affect the main conclusion.

randomly, I use imputation by chained equations implemented via the ICE procedure in STATA (Raghunathan et al. 2001; Van Buuren and Oudshoorn 2000). The imputation process yielded five imputed samples of 4,460 cases. Compared to children in the case-complete sample, those with missing values were more likely to receive free lunch, live in unsafe neighborhoods, and have lower math scores in kindergarten.

Method

The analysis consisted of three steps: OLS regression, propensity score matching, and sensitivity analysis. I began with OLS regression, predicting the effect of obesity on test scores, net of all confounding variables. The OLS estimates provide benchmarks for the estimates of the obesity penalty in both reading and math.

To reduce the bias associated with measured covariates, I use propensity score matching to estimate the average treatment effect of obesity on test scores. Propensity score matching assumes that unmeasured variables do not correlate with children's propensity to be obese or with test scores. The validity of matching estimates relies on the balance in the distributions of covariates between obese students and their normal-weight counterparts. I adopt three strategies to ensure high-quality matching: a clear definition of the treatment and control groups, controls for comprehensive covariates, and the adoption of various matching regimes (Morgan and Harding 2006). The first strategy was to implement clear definitions of the treatment and control groups. I define the treatment category as "being obese" if a child's BMI was equal to or above the 95^{th} percentile of the BMI z-score distribution in both fifth and eighth grade.[4] The control group includes children whose BMI z-scores were between the 5^{th} and the 75^{th} percentiles of the distribution.[5] The educational outcomes are IRT-scale test scores in reading and math in eighth grade. Hence, the causal question is: Does obesity depress test scores among eighth graders?

The second strategy I used to ensure high-quality matching was to control for confounding variables. Three theoretical considerations guided the selection of covariates: (1) all confounding were derived from theories and endorsed by empirical evidence; (2) all confounding variables preceded and determined the probability of being obese, those that are consequences of being obese were excluded (Morgan and Winship 2007); and (3) all confounding variables determined test scores (Angrist and Hahn 2004). In accordance with these three rules, I followed the ecological theory of childhood obesity (Procter 2007) and identified a set of individual, social, cultural, and environmental determinants of obesity, including birth weight, food and drink

[4] The number of children in the treatment and control groups remained relatively stable (>90 percent) between fifth grade and eighth grade. Only 106 of 1,400 obese children lost weight and moved into the normal-weight group, while 200 of 3,000 normal-weight children gained weight and moved into the obese group. To test the sensitivity of the treatment definition, I also examined whether being extremely obese ($\geq 97^{th}$ percentile of BMI z-scores) was more harmful to test scores than being obese ($\geq 95^{th}$ percentile of BMI z-scores) .

[5] This narrow definition of the control group is more meaningful than the more commonly used category (5^{th} -85^{th} percentile) for two reasons. First, I defined the control group based on a plot of the quadratic relationship between BMI z-scores and test scores. Second, large variations in the quadratic relationship between the 75th and 85th percentile of the BMI distribution suggest differences within this group. Despite these advantages, I also used the alternative definition of normal weight (5^{th}-85^{th} percentile) to test the sensitivity of matching estimates based on the narrowly defined control group (5^{th}-75^{th} percentile).

intake, exercise, family socioeconomic background, neighborhood safety, and school characteristics. These confounders occur at or before third grade. Because the treatment occurs in fifth grade, and outcomes occur in eighth grade, this selection not only meets the criteria of matching, but also alleviates the possibility of reverse causality.

The third strategy I adopted to ensure high-quality matching was to use various matching regimes. Because matching estimates may vary with changes in the selection criteria for control and treatment cases, the consistency of matching estimates across multiple matching regimes indicates robustness (Morgan and Harding 2006). After identifying the obesity penalty via matching model that achieved the best balance in the distribution of covariates between the treatment and control groups (Sekhon 2009),[6] I compared the estimated average treatment effect on the treated group across eight matching regimes. These matching regimes include nearest-neighbor matching with four variants in replacement and ratio, stratified matching, full matching, and optimal matching (Hansen 2004; Ho et al. 2007; Rosenbaum 1989). In addition to this comprehensive approach, I also evaluated the consistency of matching estimates with estimates for severe obesity $\geq 97^{th}$ percentile), estimates using an alternative definition of the control group (5^{th} -85^{th}

[6] The final matching model includes covariates, square terms, and interaction terms. I tried a variety of combinations of high-order and interaction terms before choosing this final matching model. I used the Kolmogorov-Smirnov Bootstrap p-values and the Q-Q plot to evaluate the balance in the distribution of the confounders between the treatment and control groups. I selected the matching regime that achieved the best balance in the distribution of the covariates with a fair number of matched cases, realizing that there is a tradeoff between the precision of the matches and the number of matched cases.

percentile), and estimates determined after the adjustment of missing values with multiple imputation.

To assess the robustness of the matching estimates in the face of bias related to unobserved variables, I adopted three methods, including regression adjustment of the matched data (Abadie et al. 2001), adding a pre-treatment outcome (Smith and Todd 2005), and conducting Rosenbaum bound sensitivity analysis (DiPrete and Gangl 2004). To adjust matching estimates via regression, I useed the Zelig program with the least squares model for continuous variables (Imai, King and Lau 2007), and included a reading test score in kindergarten as a pre-treatment outcome to make the difference-in-difference adjustment. Next, I used the Rosenbaum bounds method of sensitivity analysis to reveal how strong the selection bias would need to be to alter the matching estimates (Rosenbaum 2002; Rosenbaum 2005). The analysis proceeded in three steps. First, I specified the strength of the correlation between an unmeasured confounding variable and a student's propensity of being obese as gamma (Γ), expressed as log odds. Then I calculated the upper and lower bounds of matching estimates for each assumed level of Γ. Third, I identified a cutoff point of Γ that rendered the matching estimates statistically insignificant. I conducted the sensitivity tests for reading and math scores based on the Wilcoxon signed-rank test and the Hodges-Lehmann point estimate (Keele 2009). The Rosenbaum bounds approach represents the "worst-case" scenario with respect to the robustness of the matching estimates (DiPrete and Gangl 2004), because the method assumes that there is a strong relationship between an unobservable variable and test scores.

Measurement

The outcomes in this study include IRT-scale test scores in reading and math in eighth grade. The reading test measures students' skills in nine dimensions: letter recognition, beginning sounds, ending sounds, sight words, comprehension of words in context, literal inference, extrapolation, evaluation, and critical evaluation of literal works. The math test evaluates students' skills in number and shape, relative size, ordinal and sequence, addition and subtraction, division and multiplication, place value, rate and measurement, fractions, area, and volume. Reading scores have a mean of 171 points and a standard deviation of 27.6 points; math scores have a mean of 142 points and a standard deviation of 22 points. Both scores are slightly skewed toward the bottom. I convert original scores to standard deviation units to facilitate comparisons across studies. The treatment is being obese (≥ 95th percentile of the BMI z-score distribution) in both fifth and eighth grade, and the control group consists of normal-weight children (5th-75th percentile of the BMI z-score distribution).

To improve matching quality and alleviate the problem of reverse causality, I controlled covariates measured in or before third grade. That is, confounders occur before the treatment in fifth grade and the outcome in eighth grade. All covariates are measured via retrospective parental report, except soda consumption, which was reported by students. Birth weight is a continuous variable based on parental report in kindergarten. Enrollment in a free or reduced-price lunch program in school, and weekly soda consumption are two measures of nutritional intake. For weekly soda consumption, I converted the original value range (0, 1-2 times per week, 3-4 times per week, 1 time per day, 2 times per day, 3 times per day, 4 or more times per day) into a continuous variable, by taking the mid-point of each value range (0, 1.5, 3.5, 7, 14, 21 and 30 times per week). Sedentary and active behaviors measure the level of physical activity. Sedentary behavior is indicated by the total hours of viewing television, videotapes, or DVDs per week. Active behavior is measured by the number of days in a typical week children get twenty or more minutes of exercise vigorous enough to cause rapid breathing, perspiration, and a rapid heartbeat. Family socioeconomic status includes maternal education, paternal occupation, and family income. Maternal education is measured by years of schooling and father's occupation is measured by percentage of college graduates among jobholders in a specific occupation.[7] Family income is the total income of all persons in a child's household, including salaries, interest, retirement, and other sources. Neighborhood safety is a dummy variable indicating that a neighborhood is deemed safe for children to play outside. School type is a dummy variable indicating a student attends public school. A pre-treatment variable, reading IRT-scale scores in kindergarten, measures students' reading ability at school-entry.

[7] This measure follows Hauser's (2008) strategy.

Results

Observed obesity penalty and gender differences

In this section I review the descriptive analysis of the relationship between BMI z-scores and test scores in standard deviation units. Results in Figure 1 show a quadratic relationship between BMI z-scores and eighth-grade test scores for both reading and math. Obese children (≥ 95^{th} percentile) generally score below the mean, while normal-weight children (5^{th}-75^{th} percentiles) fluctuate around the mean. [8] Results in Table 1 show that the average difference between the two groups is 0.35 standard deviations in reading and 0.29 standard deviations in math, without adjusting any covariates. These differences are statistically significant per a t-test (p-values <0.00). The results for girls reveal an even more striking pattern. Obese girls have an average loss of 0.43 standard deviations in reading scores, approximately 50 percent larger than the loss among boys. Together, Figure 1 and Table 1 reveal considerable differences in reading and math test scores between obese children and their normal-weight counterparts.

It is essential to evaluate preexisting differences in confounders between the control and treatment groups before matching. Table 1 shows Kolmgorov-Smirnov (KS) Bootstrap p-values by comparing the distributions of covariates used in genetic

[8] Fluctuations in the relationship between BMI and test scores for children between the 75^{th} and 85^{th} percentile BMI z-scores suggest that the often-used categorical measure of normal weight (5^{th}-85^{th} percentile) does not sufficiently reflect the obesity effect on academic achievement.

matching[9] (Sekhon 2009). The variables are ordered by types of determinants of obesity. Clearly, there are significant differences between obese and normal-weight children before matching with regard to gender, birth weight, nutrition, physical activity, parental social status and reading ability in kindergarten. Compared to their normal-weight counterparts, obese children, on average, drink more soda, watch more television, and do less intensive exercise; their mothers have fewer years of schooling and their fathers hold less prestigious jobs. Further, these preexisting differences persist in the imputed sample after adjusting for missing values (results not shown). Without adequately controlling for these preexisting differences, the OLS regression may yield biased estimates of the causal effect of obesity on academic achievement.

Obesity penalty in test scores: matching estimates

Does childhood obesity cause poor school performance? The weight stigma and physical health perspectives imply that obese children tend to earn lower test scores than their normal-weight peers. To test these theoretical arguments, I conducted OLS regression models and propensity score matching. Table 2 presents the estimated

[9] Genetic matching is a multivariate matching method that uses an evolutionary search to maximize the balance of observed covariates across matched treated and control units. It uses a search algorithm to iteratively check and improve covariate balance, thus it eliminates the need to manually and iteratively check the propensity score. and it is a generalization of propensity score and Mahalanobis Distance matching.

effects of obesity derived from OLS regression results and genetic matching[10] for the primary sample (N=2,631).

Results from the OLS regression generally support the first hypothesis, that obesity is negatively associated with test scores among eighth graders. Column 1 of Table 2 shows that, compared to their normal-weight peers (BMI z-score is between 5th and 75th of the distribution), obese children have an average loss of 0.105 standard deviations in reading and 0.091 standard deviations in math in eighth grade. These estimated obesity penalties are considerably large, equivalent to the impact of reducing maternal education by two years. These estimates must be interpreted cautiously, however, as the case-complete sample includes children whose chances of gaining weight vary substantially. The estimates could also be biased if there are unmeasured variables that determine both the propensity of being obese and poor school performance.

To minimize bias related to observable variables, I use propensity score matching to adjust an individual's propensity of being obese, and to reduce the preexisting differences between obese students and their normal-weight counterparts. As shown in the Table 1 and Appendix Figure 1, among a number of matching regimes applied, genetic matching yields the best balance in the distributions of

[10] Before reporting the matching estimates, it is necessary to evaluate the matching quality. Genetic matching significantly improved the balance in the distribution of covariates between obese and normal-weight children. Table 1 compares the standardized bias of the covariates before and after genetic matching for the primary sample. The KS Bootstrap p-values for all covariates and associated interaction/ high-order terms are at or above the 0.05 significance level, therefore, the distributions of all covariates are balanced between obese and normal-weight children.

covariates between obese students and their thinner peers. That is, obese students are similar to their thinner peers in terms of age, gender, birth weight, nutritional intake, physical activity, family socioeconomic background, neighborhood, school and initial reading ability. Results in the Column 3 of Table 2 show that, once obese students were similar to their thinner peers, they on average scored 0.17 standard deviations lower in reading and 0.16 standard deviations lower in math. Results from the genetic matching model reveal larger obesity penalties than the OLS regression, because matching excludes hundreds of normal-weight students whose chances of being obese are different from their obese peers. The obesity penalties found in this study are consistent with prior reports using data from the Add Health and the children sample of the NSLY 1979(Averett and Stifel 2010; Crosnoe and Muller 2004; Sabia 2007).

How large are the obesity gaps? In eighth grade, African American students on average scored 26.7 points or 0.97 standard deviations lower in reading than their white counterparts. The black-white gap in math was 21.3 points or 0.97 standard deviations. Thus, an obesity gap of 0.17 standard deviations in reading is equivalent to 17 percent of the racial achievement gap in eighth grade, and the obesity penalty in math is approximately one sixth of the racial achievement gap. Yet, these obesity penalties are smaller than those reported by Averett and Stifel (2010), probably due to differences in age groups, sample coverage and covariates between the two studies.

To further test the consistency of the matching estimates in the context of potential bias from observed variables, I compared the estimated obesity penalties across eight matching schemes ranging from strict to lenient distance choice.[11] Figure 2 depicts the estimated obesity penalties in reading and their 95 percent confidence intervals across the eight matching regimes. Overlapping confidence intervals suggest marked consistency among the estimated obesity penalties in reading. These estimates range from a loss of 0.09 to 0.17 standard deviations. The stricter the selection criteria, the fewer control cases selected, and the greater the deviation between the estimates. Figure 3 shows similar variations in the case of math scores, which range from a decrease of 0.09 to 0.15 standard deviations. Taken together, the small fluctuations in the obesity effects across the eight matching schemes indicate that the estimated obesity penalties in reading and math are fairly consistent.

Sensitivity analysis of the obesity penalty in test scores

Despite the consistent obesity penalty in the matching models, the validity of the matching estimates may be questionable if they are affected by unobserved covariates. To explore the robustness of the matching estimates in the context of bias associated with unobserved variables, I calculate the Rosenbaum bounds for the estimated average treatment effects of obesity in reading and math, and report the

[11] The estimated treatment effects were calculated based on eight matching regimes: nearest neighbor (NN) without replacement (control-to-match ratio=1), NN with replacement (control-to-match ratio=2, caliper=0.25), NN with replacement (control-to-match ratio=2, caliper=0.5), stratified matching, full matching, optimal matching, genetic matching (control-to-match ratio=1), and genetic matching (control-to-match ratio=2). Full matching is a special form of stratified matching, and genetic matching is a special form of optimal matching (Ho et al. 2007).

results in Table 3. Column 1 of Table 3 reflects the assumed odds ratio of being obese (Γ) associated with an unmeasured variable (such as intelligence). Columns 2-4 of Table 3 show the lower and upper bounds of the Hodges-Lehmann estimates and the maximum p-values for the Wilcoxon signed-rank test. An upper bound of zero or a p-value above 0.05 indicates a critical level of Γ that renders the matching estimates invalid.

Results from Table 3 reveal that the estimated treatment effect of obesity on reading scores among eighth graders is relatively robust to biases related to unmeasured variables. To illustrate the results, consider intelligence, an unmeasured covariate that may simultaneously determine a student's propensity of being obese and school performance. If the student's intelligence is not associated with his chance of being obese (Γ=1), the estimated average treatment effect of obesity on reading (-0.17 standard deviations) from the random experiment remains valid. However, the negative impact of obesity would become insignificant if intelligence elevated the odds of becoming obese by 20 percent (Γ=1.20), judging by the 0.07 p-values from the Wilcoxon signed-rank test. In the case of the Hodges-Lehmann test, intelligence would have to increase the odds of becoming obese by 10 percent (Γ=1.10) for the upper bound of the Hodges-Lehmann estimates to move near zero. Further, in the case of math, the Hodges-Lehmann test requires that intelligence boosts the student's odds of becoming obese at least by 15 percent. Notably, the Rosenbaum bounds are a "worst-case" scenario in which an unmeasured confounding variable correlates strongly with test scores (DiPrete and Gangl 2004). Thus, it is reasonable to conclude that the causal effects of obesity on reading and math test scores for eighth graders are relatively robust against selection bias.

What does a Γ value of 1.20 mean in practice? To illustrate its magnitude, I express the selection bias designated by specific levels of Γ in terms of the equivalent effects of observed covariates on treatment assignment from the propensity score model,[12] following the strategy described in DiPrete and Gangl (2004). Columns 5-7 of Table 3 present the selection bias equivalent values. The critical level of $\Gamma = 1.20$ is attained at a difference of 12 ounces of birth weight. That is, the estimated causal impact of obesity on reading and math scores would be questionable if an unmeasured confounder (such as intelligence) affected the odds of being obese in the same magnitude as increasing the birth weight of a new-born by 12 ounces.

In conclusion, the estimated average treatment effects of obesity on reading and math among eighth graders determined via propensity score matching models are relatively robust to possible selection bias. Findings from the sensitivity analysis lend support to the causal link between childhood obesity and poor test scores.

Gender differentials

Compared to obese boys, stronger social stigma and lower educational expectations among obese girls suggest a larger obesity penalty for girls' test scores. To test this hypothesis, I added gender interaction terms to the model to examine whether obesity

[12] Table A1 in the appendix reports the specific estimates in log-odds ratio.

differences vary by gender. Because the gender interaction terms were highly significant in the OLS regression (p-values<0.05), I divided the primary sample into boys and girls, and present gender-specific matching estimates in Table 4.

As expected, the results reveal clear gender differences in the obesity penalties for test scores. As is shown in Column 2 of Table 4, obese girls, on average, score 0.221 standard deviations lower in reading and 0.214 standard deviations lower in math than their normal-weight peers. For boys, the size of the obesity penalty for math is 20 percent smaller than for girls; the obesity difference on reading scores among boys is insignificant and trivial. The estimated obesity penalties for test scores produced by the imputed values follow a similar pattern (results not shown). Overall, these findings support the second hypothesis that being obese has larger negative impacts for girls than for boys.

Calculations of the Rosenbaum bounds also reveal striking gender differences in the robustness of matching estimates. As shown in Columns 3-4 of Table 4, the matching estimates for boys are fairly weak, oscillating around zero. In contrast, the estimates for girls are relatively robust in the face of selection bias. According to the Wilcoxon signed-rank test, a selection bias of Γ around 1.35 would be necessary to render the negative effects of obesity on reading and math among girls spurious. This magnitude of selection bias equals the impact of the 1.30 pounds of birth weight, 5.0 hours of television viewing per week, or 3.4 days of intensive exercise per week. Similarly, in the case of math, an unobserved measure (such as intelligence) would have to increase the probability of being obese by 30 percent to make the matching estimates invalid. In addition, analysis of the imputed samples shows that, for both boys and girls, the negative impacts of obesity on reading scores are comparable between the case-complete sample and the imputed samples (results not shown). In summary, the striking gender differences in the findings of the matching and sensitivity analyses further confirm the second hypothesis that obese girls suffer more from heavy weight than boys with regard to school performance.

Robustness check

To further check the robustness of the matching estimates, I assessed the effects of both alternative definitions of normal weight and severe obesity and the adjustment of missing values on the estimated obesity penalties. A high level of consistency of matching estimates across these comparisons will help confirm the validity of these estimates. First, the definition of normal weight (5^{th}-75^{th} percentile) in the primary analytic sample excludes children whose BMI z-scores fall between the 75^{th} and 85^{th} percentile. Therefore, this exclusion may overestimate the obesity penalties in reading and math. Second, the definition of obesity ($\geq 95^{th}$ percentile) in the primary sample may mask the severity of extreme obesity. If obesity has a negative impact on academic achievement, extremely heavy children ($\geq 97^{th}$ percentile) are expected to suffer more from excessive weight. Thus, matching estimates using the 95^{th} percentile as a cut-off point may underestimate the impact of extreme obesity. Third, the primary analytic sample excludes students with missing values on covariates. If children who have missing values for television viewing are less likely to be obese, the estimates derived from the primary sample may overestimate the obesity penalty by excluding these children. To test these possibilities, I used the imputed samples and ran the same matching models for the primary analytic sample with alternative specifications of normal weight (5^{th}-85^{th} percentile) and severe obesity ($\geq 97^{th}$ percentile).[13]

As expected, results in Table 2 show that the estimated obesity penalties in reading and math decline slightly but remain quite large when the alternative specification of normal weight (5^{th}-85^{th} percentile) is used. For instance, obese children, on average, score 0.136 standard deviations lower in reading than their normal-weight peers (5^{th}-85^{th} percentile). This result translates into a roughly 20 percent reduction in the estimated obesity gap, compared to results using the more stringent category of normal weight. In the case of math, changing the definition of normal weight leads to a 5 percent reduction in obesity differences. Overall, these results suggest that the estimated negative impact of obesity on test scores is relatively stable, regardless of the definition of normal weight.

Further, larger impacts of heavy weight among extremely obese children ($\geq 97^{th}$ percentile) are evident in the last column of Table 2. Compared to their normal-weight peers, extremely obese children have an average loss of 0.23 standard deviations in reading and math scores. These estimates indicate a nearly 34 percent increase in the estimated obesity penalty in reading and a 50 percent increase in math.

[13] I used the ICE command in STATA to implement multivariate imputation.

These findings suggest a dose-response relationship between obesity and poor test scores—as the degree of obesity goes up, the extent of the obesity penalty increases accordingly. Thus, these findings lend additional support to the causal effect of obesity on test scores.

Finally, the obesity penalties remain substantial after adjusting for missing values in the confounding variables. Table A2 in the appendix reports the average estimates and associated standard errors for the five imputed samples.[14] Indeed, relative to their normal-weight peers, obese children scored 0.127 standard deviations lower in reading and 0.117 standard deviations lower in math. These obesity penalties are roughly 20 percent lower than those in the complete-case sample. In short, the adjustment of missing values slightly reduces the estimated obesity penalties in reading and math.

Discussion and conclusion

Childhood obesity is not only a public health crisis, but may also have far-reaching influences on the status attainment process. However, empirical investigations of obesity and school performance have often suffered from selection bias and omitted-variable bias. By applying propensity score matching to data from the Early Childhood Longitudinal Study, I demonstrate that obese eighth graders score, on average, 0.17 standard deviations lower on reading tests and 0.16 standard deviations lower on math tests, differences that equal roughly one sixth of the black-white

[14] I used Rubin's correction method to calculate the average effect of obesity and associated standard errors across the five imputed samples (Allison 2001, p. 30)

achievement gap. The estimated harmful effects of obesity on academic performance are relatively robust in the face of hidden bias, and findings from sensitivity analyses reveal that an unmeasured confounder must increase the odds of becoming obese by at least 20 percent to alter the conclusions. Obesity penalties in reading and math test scores are stronger for girls than for boys. The estimated obesity penalties in test scores are relatively consistent across the eight matching regimes; however, the penalties decline slightly after adjusting for the missing values in the confounders and using an alternative definition of normal weight (5^{th}-85^{th} percentile). In sum, these findings support the weight stigma and physical health perspectives whose proponents assert that obesity has a negative impact on academic achievement. The findings provide compelling evidence for the necessity of policy interventions that seek to reduce childhood obesity, such as the “Let’s Move” campaign.

The current findings are consistent with prior reports using data from Add Health (Crosnoe and Muller 2004; Sabia 2007), the CNLSY79 (Averett and Stifel 2010), and earlier waves of the ECLS-K(Cesur and Kelly 2010), as well as a study using genetic markers as instruments (Ding et al. 2009). However, the size of the obesity gaps in reading and math are smaller than those reported by Averett and Stifel (2010), whose estimates of the obesity penalties in math were roughly 0.71 standard deviations. In addition to differences in age groups and sample coverage, one possible reason for the difference is that in this study I controlled for nutritional intake, physical exercise, and neighborhood safety, while these data were not available in the sample used by Averett and Stifel (2010).

In addition, the larger negative impact of obesity among girls is consistent with prior findings using Add Health data (Sabia 2007), and the research using genetic markers as instruments (Ding et al. 2009). However, results differ from those of a study using the first-grade data from ECLS-K, which suggested a larger penalty for boys than for girls (Datar, Sturm and Magnabosco 2004). Two factors may account for larger obesity penalties among girls in the current study.[15] First, this study focuses on the test scores of eighth graders (ages 14-15) while the sample used by Datar, Sturm, and Magnabosco (2004) consisted of first graders (ages 6-7). Prior studies have documented that negative stereotypes about obese individuals increase with age (Lerner, Karabenick and Meisels 1975). Therefore, larger obesity effects for girls than boys at older ages are not surprising. Second, differences in estimation methods and sample may partially explain the discrepancies. Datar, Sturm, and Magnabosco (2004) used OLS methods with a variable for prior weight status, whereas the matching method used in this study restricted the sample to a group of normal-weight and obese children who had comparable distributions of confounders. Hence, the current estimates of the average treatment effects of obesity on test scores reveal larger negative impacts of obesity among girls.

Through what mechanisms does obesity lead to poor test scores? Proponents of the social stigma and health problem perspectives have proposed three mechanisms: behavior problems (Crosnoe 2007), low educational expectations

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[15] I defined the control group as children whose BMI z-scores fell between the 5th and the 75th percentile, a much narrower definition than the control group (5th-85th percentile of BMI z-scores) in Datar, Sturm, and Magnabosco (2004) .

(Crandall 1995), and school absenteeism due to obesity-related health problems (Geier et al. 2007). The rich information in ECLS-K allows a test of these mechanisms (results not shown), with the exception of weight discrimination. Although the ECLS-K has no direct measures of weight discrimination, the survey did ask parents to report whether their children were often "picked on" or bullied in eighth grade.[16] Because some bullying behaviors are a form of severe weight discrimination, the data from this question can serve as a proxy measure of the degree of weight discrimination. The preliminary findings support the proposition that obesity operates through all three mechanisms. Compared to their normal-weight peers, obese children are 22 percent more likely to report being bullied, 22 percent more likely to report being worried, 23 percent more likely to complain of illness, and 14 percent less likely to expect to receive a bachelor's degree. Thus, I expect that school absenteeism, behavior problems, and low educational expectations are potential causal pathways influencing the academic performance of obese students during childhood.

Based on a recent search of the literature, this is the first empirical paper using propensity score matching and sensitivity analysis to examine the causal impact of childhood obesity on academic achievement. The strength of this study lies in three aspects that confirm the validity of obesity penalty estimates. First, results from propensity-score-matching models reveal a causal link between obesity and poor school performance. A relatively comprehensive set of determinants improved the

[16] It is unclear whether the bullying behavior is specifically weight-based, and whether the bullying is verbal or physical.

validity of matching estimates in the face of bias from observable variables and reverse causality. In particular, unlike previous studies, I controlled for measures of nutrition, exercise level, and neighborhood safety. Covariates that occurred before treatment have strong explanatory power to predict both the treatment and the outcomes—they explain three fifths of the variation in reading test scores and more than half of the variation in math scores; the impact of the covariates on the probability of becoming obese is statistically significant and substantial in practice (appendix Table A1). Overall, these strategies yield valid matching estimates. Second, I explicitly evaluated the ways selection bias affects the validity of obesity penalties via Rosenbaum bounds. My methodological contribution is to show how large selection on unobserved variables would need to invalidate the entire obesity effect. It shows that the matching estimates remain valid unless an unobserved variable increases the chance of being obese by at least 20%. With a Rosenbaum bounds test, I provide a lower-bound estimate of the obesity effect on reading and math scores. Third, the causal link is further reinforced by the observation of striking gender differentials in obesity penalties, and a dose-response relationship between the degree of obesity and lower test scores. Additionally, matching estimates are insensitive to the specifications of matching regimes, the imputation of missing values, and analysis with alternative specifications of normal weight.

The obesity penalty for academic achievement during childhood has important implications for social stratification at both the individual and the population level. At the individual level, if early onset of obesity negatively affects cognitive development, when obese children grow up to be obese adults (Whitaker et al. 1997), they will likely acquire fewer skills that are highly valued in the labor market and therefore will earn less. A growing body of research has demonstrated that weight accounts for a sizable portion of earning inequality in adulthood, net of intelligence and family socioeconomic background (Judge and Cable 2004; Loh 1993). At the population level, if rates of obesity continue to rise from childhood to adulthood in the United States, and the population consists of a large proportion of obese adults with lower levels of productivity, the overall competitiveness of the labor force will be severely compromised in the near future. Thus, policies that effectively promote physical education and reduce weight stigma are sorely needed to prevent the deleterious impacts of childhood obesity.

This study generates need for future research to advance the scholarly understanding of the causal effects of childhood obesity on academic achievement. First, while propensity score matching and sensitivity analyses provide a way to assess the selection bias, these methods do not completely alleviate biases related to unmeasured variables. Recognizing that the process of becoming obese is not random in observational data, researchers should collect data and control certain measures that are unavailable in the ELCS-K data, such as intelligence, biomarkers, and obesity-related genetic factors. Norton and Han (2008) advanced the field by examining the association between adult obesity and wages and including obesity-related genetic factors, yet further data and studies are needed to improve the scholarly understanding of this relationship. Second, public perceptions of obesity vary by geographic concentration and may change with the rising prevalence of obesity. A recent report shows substantial geographic variability of childhood obesity at the county level (Centers for Disease Control and Prevention 2010). Discovering how these patterns lessen (or elevate) obesity penalties will require further investigation. Third, future studies should also consider potential racial differences in the obesity gap in academic achievement. African American and Hispanic children face less weight stigma within their communities, probably due to disproportionately high prevalence of obesity(Puhl and Heuer 2009), yet they possess fewer financial resources to fight obesity and have reduced educational expectations. Thus, it is crucial to explore racial differentials in obesity penalties with respect to academic achievement. Fourth, it is important to recognize that medical researchers may consider weight status as a continuous or ordinal variable, rather than a binary variable (Imai and van Dyk 2004). Future application of propensity score matching to multiple treatments will advance our understanding of the complex process generating obesity penalty in school performance.

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Table 1. Summary statistics for two sample t-tests comparing obese to normal weight children before and after matching for the primary sample (N=2,631)

Variables		Mean		KS Bootstrap p-value[a]	
		Treatment[b]	Control	Before Matching	After Matching
Reading (SD)		-0.17	0.18		
	Girls	-0.14	0.29		
	Boys	-0.18	0.08		
Math (SD)		-0.06	0.23		
	Girls	-0.17	0.17		
	Boys	0.01	0.28		
Girl		0.40	0.49	0.000	0.655
Age		11.07	11.08	0.520	0.377
Birth Weight (pounds)		7.66	7.39	< 2.22e-16	0.047
Free or Reduced Priced Lunch		0.36	0.21	0.000	0.157
Weekly Soda Consumption(times)		6.01	5.94	0.307	0.560
Weekly 20-minute Intensive Exercise (days)		3.79	4.14	< 2.22e-16	0.330
Weekly TV viewing (hours)		7.62	6.36	< 2.22e-16	0.502
Family Income (log)		10.54	10.88	< 2.22e-16	0.045
Mother's Years of Schooling		13.12	14.21	< 2.22e-16	0.211
Father's Occupation(% college graduates)		0.18	0.29	< 2.22e-16	0.383
Unsafe Neighborhood		0.20	0.15	0.010	1.000
Public School		0.86	0.78	0.000	0.317
Reading Scores at Kindergarten		28.25	31.70	< 2.22e-16	0.086
Age^2		122.75	122.97	0.520	0.377
Age×Birth Weight		84.84	81.88	< 2.22e-16	0.044
Mother's Education ^{2}		178.88	208.28	< 2.22e-16	0.211
Public School×Age		9.56	8.59	< 2.22e-16	0.416
Public School×Mother's Education		11.23	10.80	< 2.22e-16	0.24
Public School×Father's Occupation		0.14	0.21	< 2.22e-16	0.479

Source:The Early Childhood Longitudinal Study-Kindergarten Eighth Grade Public-Use Data (2006)

Note: [a]The Kolmogorov-Smirnov(KS) Bootstrap p-value measures the balance of the distribution of a continuous covariate between the treatment and the control group in genetic matching (Sekhon 2011). A KS Boot of tests p-value is equal to the T-test p-value for a dummy covariate. In both cases, a p-value below 0.05 indicates statistical significance.

[b]The treatment group is obese children (≥95th percentile) and the control group is normal-weight children (5th-75th percentile).

Table 2. Estimated effects of obesity on eighth graders' test scores in 2006 for the primary sample.

	OLS[a]	Genetic Matching[b]		
	Obese (≥95th) vs. Normal (5th -75th)	Obese (≥95th) vs. Normal (5th -85th)	Obese (≥95th) vs. Normal (5th -75th)	Extreme Obese (≥97th) vs. Normal (5th -75th)
Reading	-0.105**	-0.138**	-0.170***	-0.229***
	(0.048)	(0.063)	(0.054)	(0.079)
Math	-0.091**	-0.149***	-0.157**	-0.228***
	(0.039)	(0.051)	(0.056)	(0.066)
N	2,631	1,236	1,224	794

Source: The Early Childhood Longitudinal Study-Kindergarten Eighth Grade Public-Use Data (2006)
Note:
[a] The OLS regressions for reading and math control the same covariates as those used in the genetic matching (gender, age, birth weight, reduced lunch, soda consumption, intensive exercise, TV viewing, low income, mother's education, father's occupation, neighborhood safety, school type, age^2, age*birth weight, momed^2, public*age, public*college, and public*momed,).
[b] Genetic matching achieves the best balance in the distributions of covariates between treatment and control group (Sekhon2011).

Table 3.Rosenbaum Bound sensitivity test for the obesity penalty in test scores for the primary sample (N=1,236)

	Rosenbaum Bounds[a]				Hidden Bias Equivalent[b]
	Gamma (Γ)	Lower. Bound HL Est.	Upper. Bound HL Est.	p-values for Wilcoxon Signed-rank Test	Birth Weight (Ounces)
Reading					
	1.00	-0.15	-0.15	0.00	0.00
	1.05	-0.25	-0.05	0.00	3.36
	1.10	-0.35	0.05	0.01	6.56
	1.15	-0.45	0.15	0.03	9.60
	1.20	-0.55	0.25	0.07	12.48
	1.25	-0.65	0.35	0.15	15.36
Math					
	1.00	-0.16	-0.16	0.00	0.00
	1.05	-0.26	-0.06	0.00	3.36
	1.10	-0.36	0.04	0.01	6.56
	1.15	-0.46	0.14	0.03	9.60
	1.20	-0.56	0.24	0.08	12.48
	1.25	-0.66	0.34	0.16	15.36

Source: The Early Childhood Longitudinal Study-Kindergarten Eighth Grade Public-Use Data (2006)

Note:

[a] Column 1 of Table 3 reflects the assumption about endogeneity in the treatment assignment in terms of the odds ratio of the differential treatment assignment due to an unmeasured covariate. At each level of Γ, I calculate the lower and upper bounds of the Hodges-Lehmann point estimates of the treatment effect in the case of endogenous selection into treatment status, and the bounds for the p-critical value from the Wilcoxon signed rank test. By comparing the Rosenbaum bounds on treatment effects at different levels of Γ, I can evaluate the strength such unmeasured influences must have in order that the estimated treatment effects from propensity score matching would have arisen purely through random assignment.

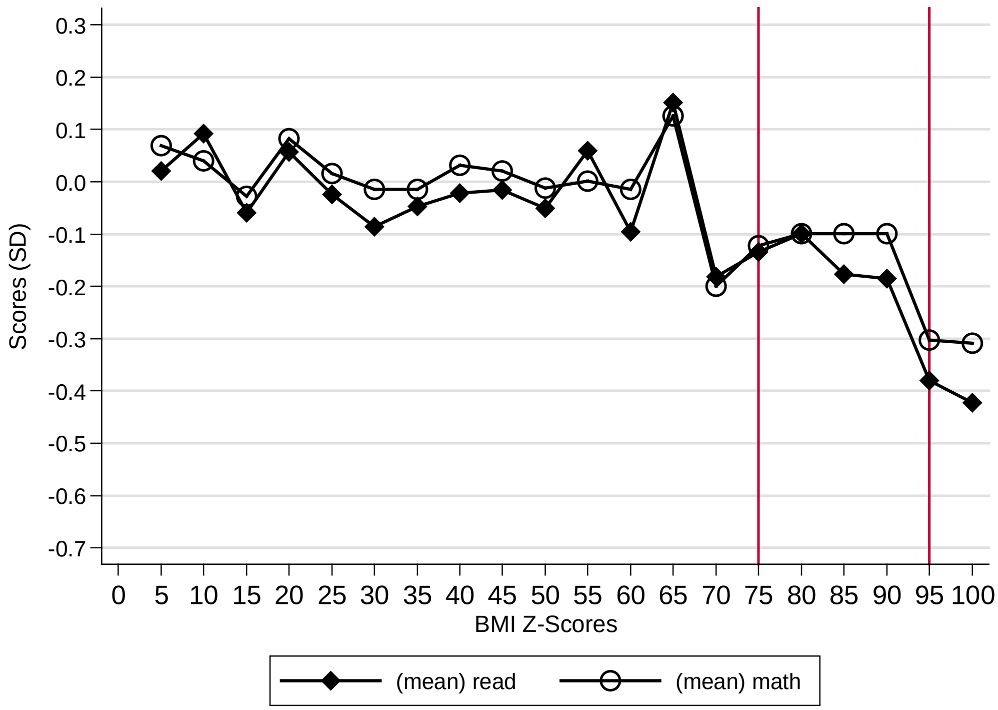
[b] I calculate the Hidden Bias equivalent with the coefficients derived from logistic regression of obese on covariates, following DiPrete and Gangl (2004). For example, the hidden bias equivalent of Γ =1.20 is 12.48 ounces (i.e. 0.78 pounds) increase in birth weight (i.e. $\log(\Gamma)$ / β(birth weight) = log(1.20)/0.23 = 0.78).

Table 4.Matching estimates of obesity penalty and sensitivity analysis for boys and girls (N=2,631)

		Estimates		Sensitivity Analysis	
		OLS[a] β	Genetic Matching ATT	Hodges-Lehmann Point Estimate	Wilcoxon Signed Rank P-Value
Boys					
	Reading	-0.037	-0.042	1.05	1.00
		(0.060)	(0.097)		
	Math	-0.087	-0.161**	1.10	1.10
		(0.053)	(0.077)		
	N	1405	750		
Girls					
	Reading	-0.140	-0.221**	1.15	1.35
		(0.069)	(0.095)		
	Math	-0.093	-0.214**	1.15	1.30
		(0.064)	(0.080)		
	N	1247	446		

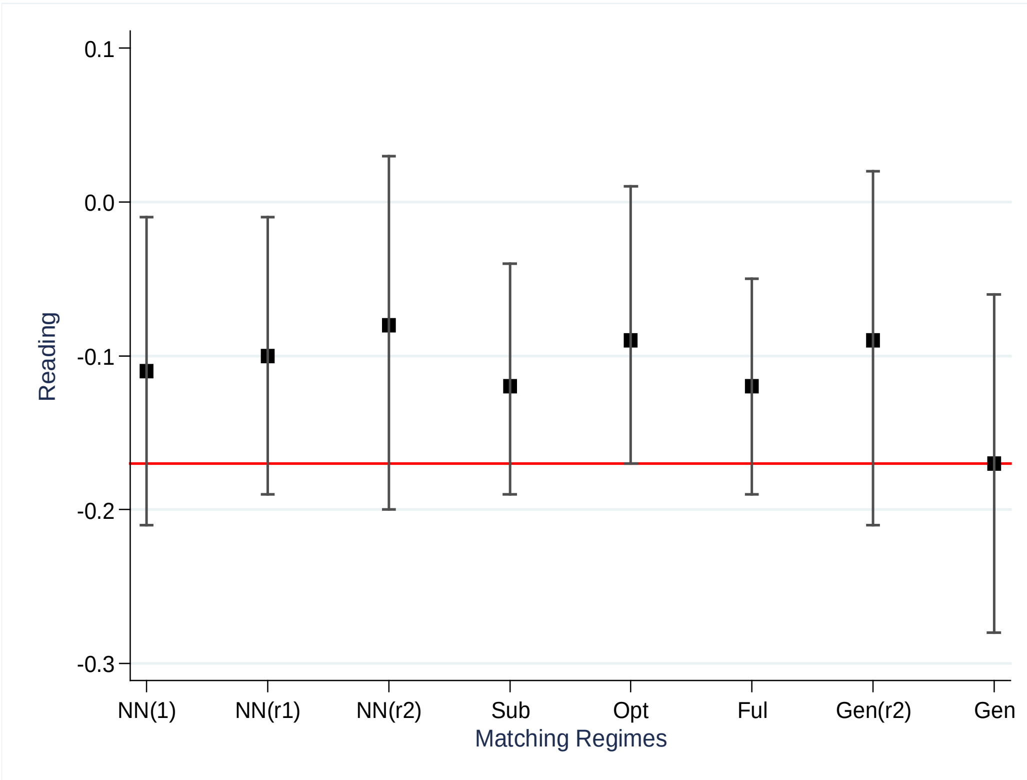
Source: The Early Childhood Longitudinal Study-Kindergarten Eighth Grade Public-Use Data (2006)
Note:
[a] The interaction term of gender and obesity in the OLS regressions of reading and math for the entire sample appears to statistically significant.

Figure 1. The quadratic relationships between the BMI z-score and test scores at eighth grade in 2006



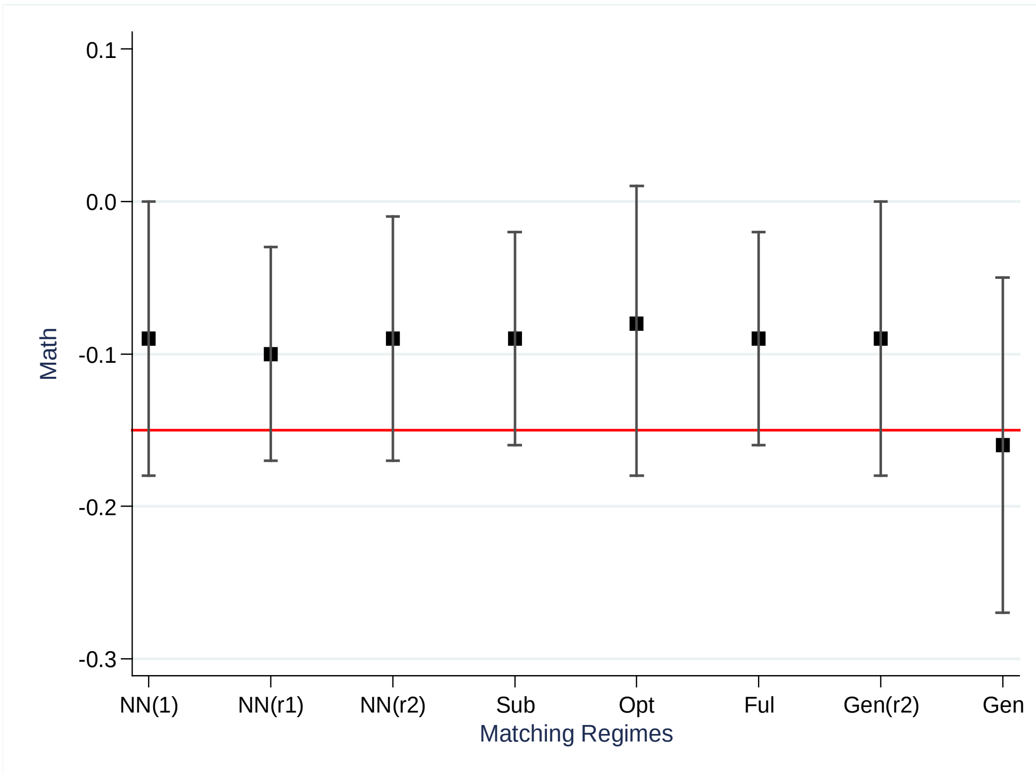
Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data

Figure 2.The estimated obesity penalties in reading scores across eight matching regimes



Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data

Figure 3.The estimated obesity penalties in math scores across eight matching regimes



Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data

Appendices

Table A1. Logistic regression of being obese for the primary sample

Explanatory variables	Obese at fifth/eighth grade (≥95th percentile BMI)
Girl	-0.368***
	(0.101)
Age	0.057
	(0.144)
Birth Weight (lbs)	0.223***
	(0.041)
Free or Reduced Priced Lunch	0.213
	(0.131)
Weekly Soda Consumption (times)	-0.011
	(0.007)
Weekly Intensive Exercise (days)	-0.093***
	(0.025)
Weekly TV Viewing (hours)	0.062***
	(0.014)
Family Income (log)	-0.260***
	(0.082)
Mother's Years of Schooling	-0.053**
	(0.024)
Father's Occupation (% college graduates)	-0.914***
	(0.227)
Neighborhood Unsafe to Play	0.032
	(0.134)
Public School	0.269*
	(0.139)
Living in North	0.185
	(0.126)
Reading IRT Scale Score at Kindergarten	-0.023***
	(0.006)
Constant	0.732
	(1.861)
Observations	2652
Log-likelihood	-1307

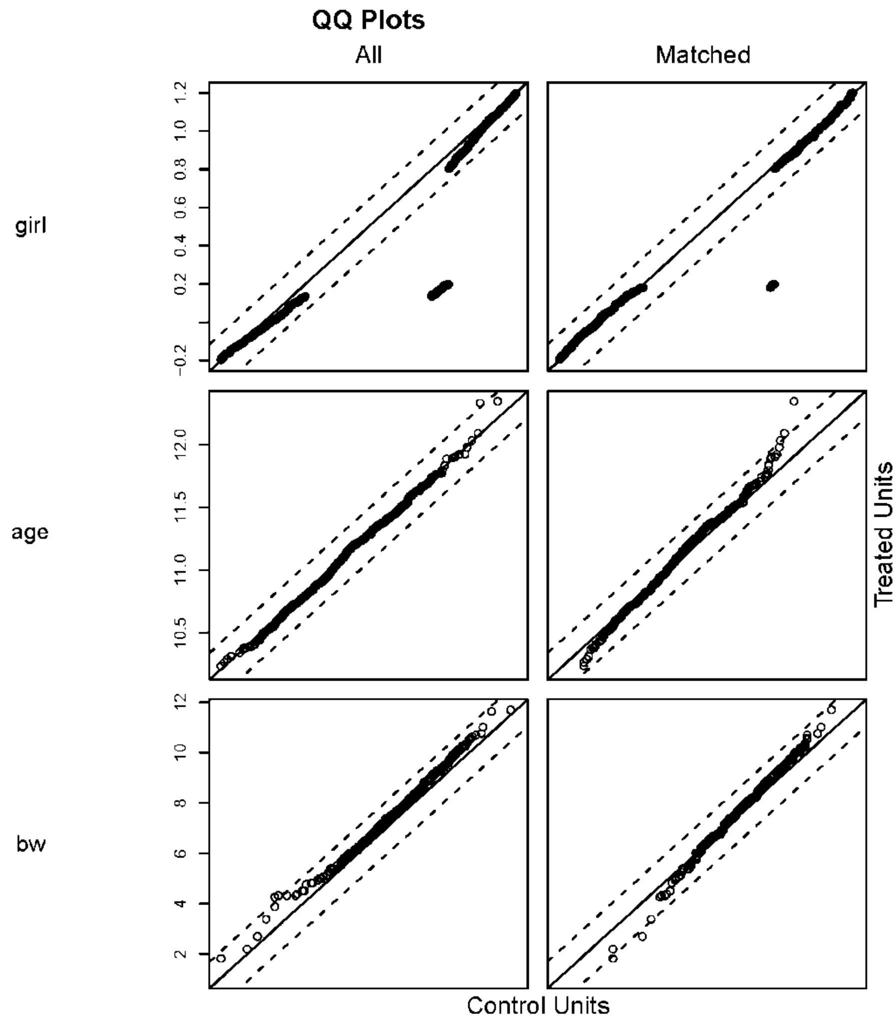
Source: The Early Childhood Longitudinal Study-Kindergarten Eighth Grade Public-Use Data (2006) .
Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

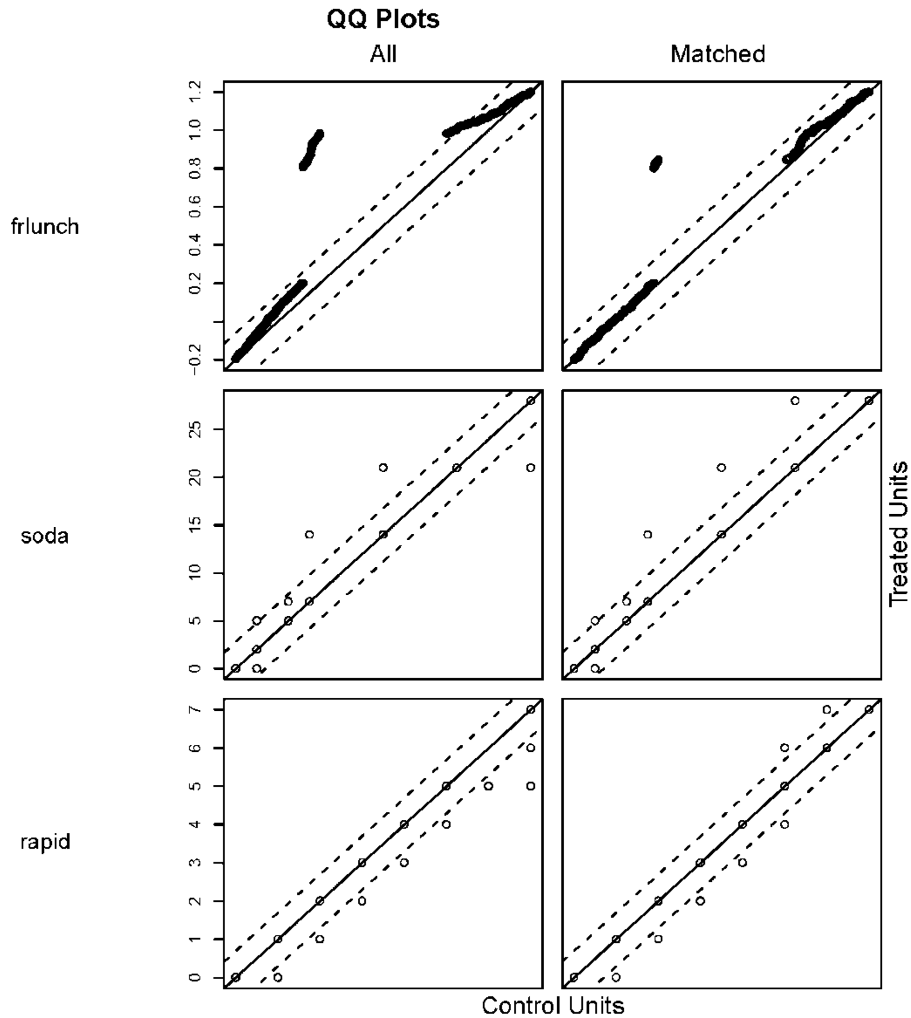
Table A2. OLS and matching estimates of obesity penalties for the imputed sample[a].

		Estimates			Sensitivity Analysis	
		OLS	Full Matching	Genetic Matching	Hodges-Lehmann Point Estimate	Wilcoxon Signed Rank P-Value
		β	ATE	ATE		
Whole						
	Reading	-0.087**	-0.085**	-0.127**	1.10	1.20
		(0.031)	(0.029)	(0.050)		
	Math	-0.042	-0.067*	-0.117**	1.10	1.20
		(0.030)	(0.030)	(0.044)		
	N	4,460	4,460	2,226		
Girls						
	Reading	-0.149***	-0.146***	-0.187***	1.30	1.30
		(0.045)	(0.041)	(0.070)		
	Math	-0.065	-0.073	-0.098	1.05	1.05
		(0.045)	(0.044)	(0.068)		
	N	2,153	2,153	926		
Boys						
	Reading	-0.049	-0.046	-0.074	1.05	1.00
		(0.043)	(0.041)	(0.065)		
	Math	-0.032	-0.067	-0.108	1.10	1.10
		(0.039)	(0.039)	(0.057)		
	N	2,307	2,307	1,340		

Source: The Early Childhood Longitudinal Study-Kindergarten Eighth Grade Public-Use Data (imputed with ICE) .
Note:
[a] I use the ICE procedure to fill in missing values in the covariates and generate five imputed datasets. I use the Rubin's correction to calculate the average estimates and standard errors across five imputed samples.
[b] Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure A1. The Quantile-Quantile plots of covariates in the genetic matching.

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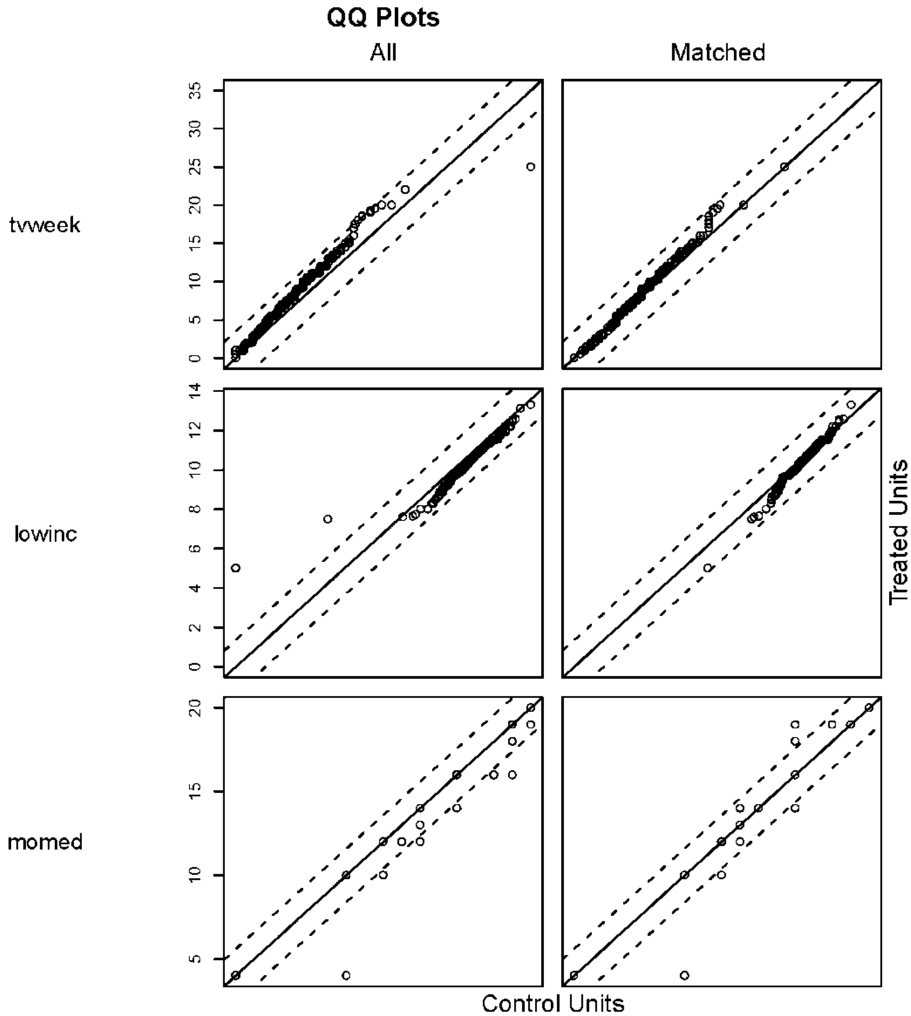
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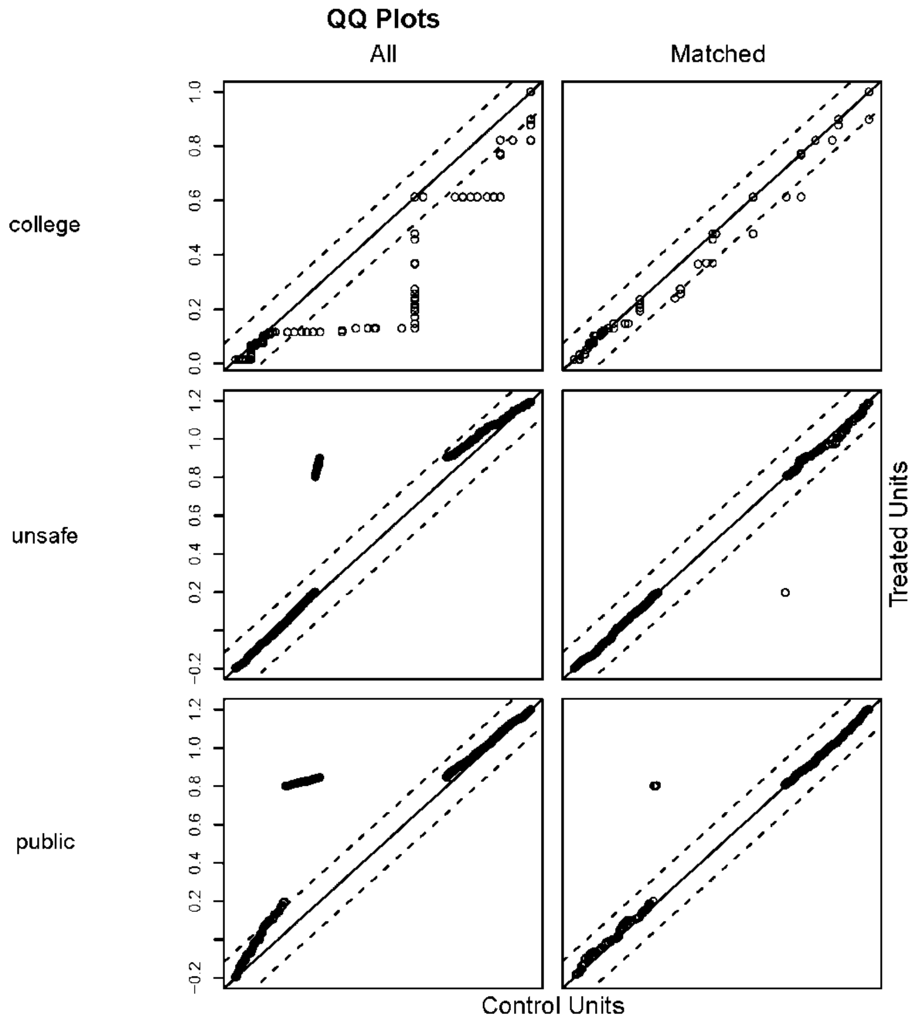

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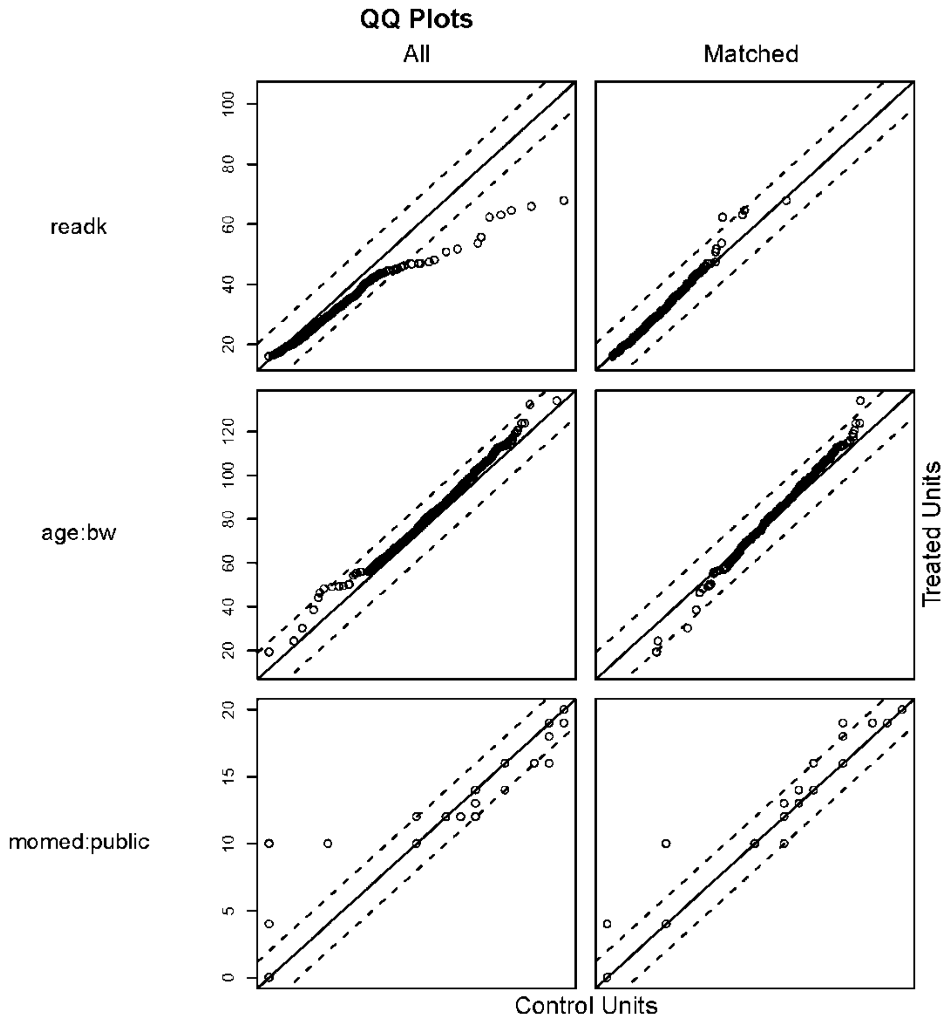
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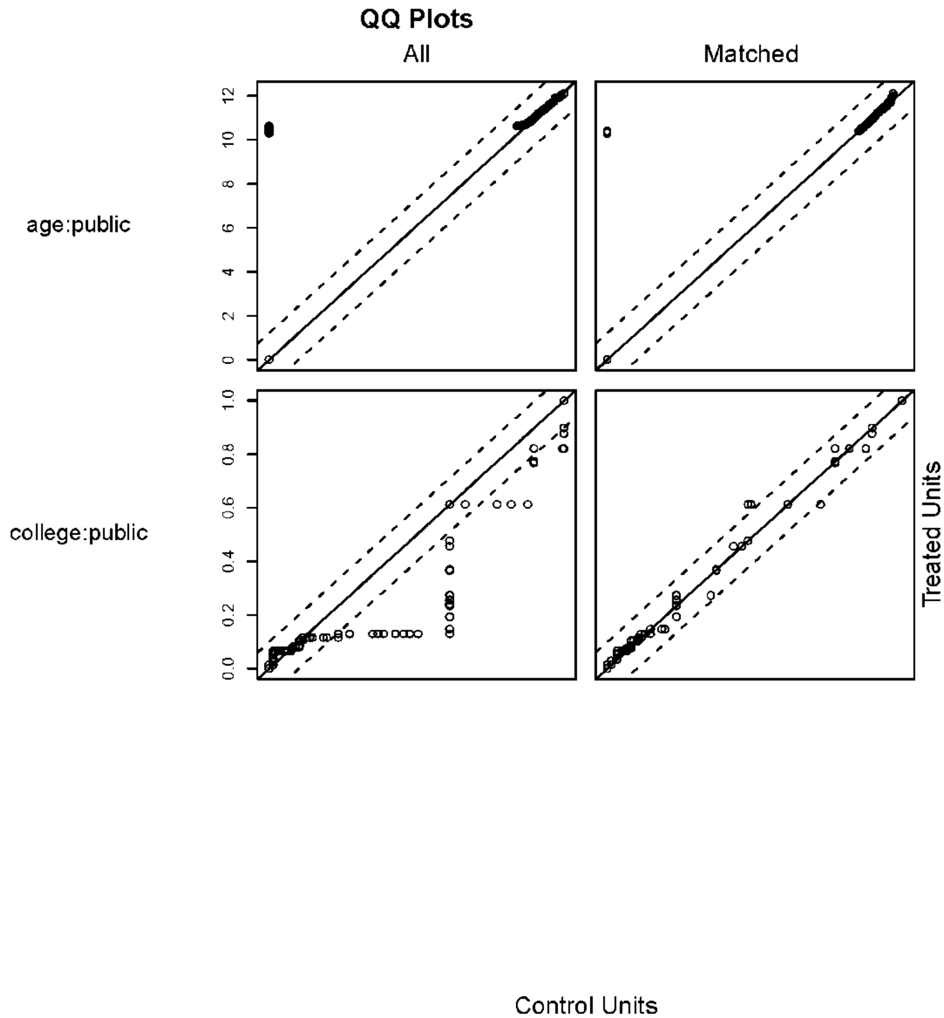
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Chapter II Pathways Leading to the Obesity Penalties in Academic Achievement

Abstract

Scholars seldom study the underlying mechanisms that link obesity and poor academic achievement. Drawing on the non-cognitive skill formation framework, I examine the ways in which work habits, behavioral problems, educational expectations, and school absences account for the obesity penalty in reading and math test scores. Using data from the Early Childhood Longitudinal Study, I show that work habits and parental educational expectations are the most important pathways leading to poor school performance among obese children, while the contributions of school absence and behavioral problems are minimal. These findings suggest that cultivating good work habits can effectively boost the academic achievement of obese children.

Key Words: Obesity, Work habits, Behavioral problems, Educational expectations, School absence, Test scores

Introduction

Scholars have consistently documented the deleterious effects of obesity on cognitive development throughout childhood and adolescence (Averett and Stifel 2010; Crosnoe 2007; Ding et al. 2009). However, little effort has been made to incorporate sociological theory into research on childhood obesity to help explain why heavy weight may hinder students' school performance. The study of causal pathways is of particular importance in the context of the current obesity epidemic; childhood obesity rates have tripled—increasing from 5 percent to 17 percent—over the past four decades (Ogden, Carroll and Flegal 2008). From 1999 to 2008, approximately one in five school-age children was classified as overweight (Ogden et al. 2010). With so many children entering school with the burden of excessive weight, examining how obesity leads to poor academic achievement is imperative.

Using a nationally representative sample of children from the Early Childhood Longitudinal Study, I expand current theoretical arguments by proposing the work habit perspective, which focuses on attention and effort in school learning. I develop a decomposition method to assess the relative role of each mechanism. Findings reveal that poor work habits and low educational expectations account for nearly half of the obesity penalties, while the role of behavioral problems and physical health are minimal. These findings not only support the theory that weight stigma (operating via work habits and educational expectations) is a source of underachievement, but also confirm the important role of non-cognitive skills in boosting academic achievement during childhood; they suggest that in addition to reducing stigma, fostering good work habits may compensate for the negative effects of obesity.

Linking obesity to academic achievement

Why might obesity depress achievement? For years, researchers have speculated about the potential harm of excessive weight during childhood, but have produced little empirical evidence. The evidence that does exist is largely indirect and inconclusive. The following section presents four explanations (school absence, behavioral problems, reduced educational expectations and work habits) of the link between obesity and educational achievement. The first three explanations represent long-held beliefs about the deleterious effects of obesity that have yet to be thoroughly tested. The work habits model is a newer perspective that synthesizes various aspects of non-cognitive skill formation theory as it applies to school achievement.

School Absence

Advocates contend that frequent school absences due to obesity-related health problems often disturb learning processes in school. Built on the notion that cognitive development depends on the amount of time spent in school and completing specific tasks, studies in the education literature have established that frequent school absences have a negative impact on test scores beginning in kindergarten (Easton and Engelhard 1982; Gottfried 2010; Romero and Lee 2007). Childhood obesity is often associated with chronic physical health problems that hinder school attendance, including sleep apnea, asthma, and cardiovascular diseases (Daniels 2008; Daniels 2006). Two studies have reported that, compared to normal-weight children, obese children have 2-3.5 more days of school absences per month (Geier et al. 2007; Schwimmer, Burwinkle and Varni 2003). Chronic health problems, such as asthma, can also exacerbate the school attendance of obese children by adding two additional days of absence per month (Bonilla et al. 2005). Thus, more frequent school absence among obese students may disrupt their learning progress in school.

Scholars report that obese children with sleep disorders tend to score worse on math tests (Daniels 2008; Perez-Chada et al. 2007). However, simply counting missed school days, without considering concentration level and work efforts, is not an adequate method of explaining the differences in academic achievement by obesity status. Effective learning depends not only on the quantity of time, but also the quality of time spent in school and classrooms (Farkas 2003). Although these chronic health problems are related to more school absences due to treatment, they may also lead to fatigue and lack of concentration in class (Currie 2009). Thus, the independent role of physical health problems in the presence of work efforts remains unclear. My study extends this hypothesis by testing the explanatory power of school absences in mediating the effect of obesity on achievement.

Behavioral Problems

In reaction to weight stigma, obese individuals develop lower levels of self-worth, self-confidence, and self-esteem, which hamper their cognitive development. Ongoing low self-esteem and depression negatively affect school readiness and the trajectory of academic growth through adolescence (Bub, McCartney and Willett 2007; Campbell et al. 2006; McLeod and Kaiser 2004). A number of studies have shown that obese children often endorse the negative stigma and stereotypes (Cramer and Steinwert 1998); constantly view themselves as incompetent, dumb, and ugly during their daily interactions with peers, teachers, and parents (Rimm and Rimm 2004); and develop more behavior problems in response to negative stereotyping and discrimination, including depression, low self-esteem, and fighting (Falkner et al. 2001; Strauss 2000; Tang-Peronard and Heitmann 2008). In short, the weight stigma model hypothesizes that behavioral problems among obese children act as barriers to fruitful cognitive development (Crosnoe 2007).

A few empirical studies have shown that low self-esteem and subsequent behavior problems mediate the obesity penalty in school performance, however, the degree of mediation has varied across studies. Findings from an Iceland study showed that controlling for depression and low self-esteem attenuated the negative of impact of body mass index (BMI) on grades (Sigfusdottir, Kristjansson and Allegrante 2007). In addition, Tershakovec and colleagues (1994) reported that, among urban

African American elementary school students, the negative effect of obesity on school performance vanished after controlling for self-esteem (Tershakovec, Weller and Gallagher 1994). Crosnoe (2007) found that one-third of the lower odds of college enrollment among obese girls was attributable to measures of externalizing behavioral problems (alcohol and marihuana use), school disengagement (class failures and unexcused school absences), and suicidal ideation (Crosnoe 2007). Thus, there is no conclusive evidence of the role of low self-esteem and behavioral problems as mediators. Additionally, a study of Arkansas elementary and middle school students showed that controlling for weight-based teasing slightly mediated the negative impact of obesity on test scores (Krukowski et al. 2009).

Reduced Educational Expectations

Reduced educational expectations among the teachers and parents of obese students, as well as among the students themselves, may link obesity to poor academic achievement. Scholars of status attainment theory argue that the power of educational expectations lies in two aspects: (a) expectations are a psychological resource that individuals draw upon when making decisions about further schooling (Haller and Portes 1973); and (b) expectations reflect a realistic calculation of the prospects for future education (Jencks, Crouse and Mueser 1983). Parental educational expectations can also translate into effective parenting practices, investment, and work efforts (Baker and Stevenson 1986; Englund et al. 2004). Thus, parental educational expectations are a strong predictor of academic achievement (Fan and Chen 2001). In the case of obesity, studies have found that obese daughters, compared to their normal-weight counterparts, received lower parental aspirations (Crandall 1995); less financial support in college (Crandall 1991); and less effective parenting with respect to monitoring, warmth, inductive reasoning, and problem solving (Simons et al. 2008). Further, obese young adults are less likely to aspire to finish college and attain prestigious occupations (Ball, Crawford and Kenardy 2004; Falkner et al. 2001). Thus, the weight stigma model suggests that lower educational expectations are the second channel leading to poor academic achievement among obese children.

No empirical investigations have tested the mediating effect of low educational expectations on the link between obesity and test scores. My study extends the current literature by both directly testing the impact of low parental educational expectations, and disentangling the relative contributions of behavioral problems and reduced parental educational expectations.

Work Habits

Obese students may also lack conscientious work habits that are essential to successful learning[17]. According to the cultural capital framework (Farkas 2003;

[17] Farkas (2003) summarized a number of the skills rewarded in the American school system. These skills include conscientious work habits, such as effort (industriousness and perseverance), organization, discipline, attendance, participation, and enthusiasm, and behavior traits (leadership,

Lareau and Weininger 2003), good work habits comprise the strategies and tactics for completing academic tasks that are honed through experience so that a student will apply them almost without thinking (Corno 2004). Specifically, good work habits are manifested in completing homework, class participation, effort, and organization (Farkas et al. 1990).

Good work habits lead to school success for three reasons. First and foremost, teachers reward effective works habit as much as or more than cognitive skills when assigning grades (Bowles and Gintis 1976; Farkas et al. 1990). Displays of work habits signal potential productivity and common cultural values endorsed by teachers. Thus, students with good work habits are easy to teach and more pleasant to interact with (Entwisle, Alexander and Olson 2005). Second, students with good work habits actively participate in the learning process (McCann and Turner 2004). As they complete their assignments, these self-regulated learners carefully select methods, make plans, organize materials, prioritize tasks, persist in the face of difficulty, self-instruct, and self-monitor their learning progress (McCann and Turner 2004). Good work habits also cultivate the development of self-confidence in academics and sustain motivation and aspirations (Paris, Byrnes and Paris 2001; Schallert, Reed and Turner 2004). The significant influence of good work habits on school success is consistent across studies sampling students from kindergarten to high school (Bodovski and Farkas 2008; Farkas et al. 1990; Lleras 2008).

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sociability, self-confidence, social sensitivity, impulsiveness, openness to experience, emotional stability, vigor, aggressiveness, disruptiveness, locus of control, and self-esteem)

Obese children are more likely than their average-weight peers to lack the good work habits needed to implement their intentions to learn in practice. Obese children are less likely to describe themselves as hard workers and twice as likely to see themselves as lazy (Rimm and Rimm 2004). For obese children, feelings of discouragement often lead to underachievement via a path of not completing homework or not studying. They protect their fragile self-concepts by making excuses, blaming teachers or parents, or claiming school work is boring (Rimm and Rimm 2004). Thus, if good work habits are the most important ingredient for academic success, a shortage of such habits among obese children may lead to school failure. Unfortunately, no past studies have explored the mediating effect of work habits in explaining the obesity gap in test scores.

Research hypotheses

My study incorporates the sociological theory of work habits and explicitly investigates the underlying mechanisms linking childhood obesity and academic achievement. I argue that, in addition to school absences, behavioral problems and reduced educational expectation, work habits exert an independent influence on the academic performance of obese students.

Adopting the work habits model expands the theoretical mechanisms in three ways. First, the model shifts attention to non-cognitive traits that are central to an effective learning process. These individual traits are under the control of students and are malleable via intervention. Second, the model emphasizes positive work habits and the actual implementation of educational expectations, which are overlooked by prior studies. Finally, the model focuses on attention and efforts in school learning that go beyond school attendance. Thus, incorporating the work habits perspective will enhance the scholarly understanding of the channels linking obesity and reduced academic achievement.

A combination of these four pathways predicts that work habits, together with behavior problems, educational expectations, and school absences are important mechanisms that explain the obesity penalty in school performance. Specifically, the combined model suggests that the negative association of obesity with test scores will be attenuated by controlling for measures of non-cognitive skills. In addition, I hypothesize that work habits are the most important mediating factor determining obesity penalties in both reading and math test scores.

Methods

Data

To test these hypotheses, I use the Early Childhood Longitudinal Study-Kindergarten cohort dataset (ECLS-K). ECLS-K is a nationally representative data set collected by the Department of Education. Beginning in the fall of 1998 when they were enrolled in kindergarten, the survey followed 21,000 children through the spring of 2006.[18] ECLS-K has several advantages for exploring the mechanisms linking obesity and academic achievement. First, the data set has relatively comprehensive and refined measures of behavioral problems, educational expectations, school absence, and work habits. In particular, the data include indicators of work habits that are not available in the children's sample of the National Longitudinal Study of Youth (CNLSY79) or the National Longitudinal Study of Adolescent Health (Add Health). The measures of internalizing behavioral problems from teachers' evaluations in ECLS-K have a higher degree of reliability than the Add Health reports from parents or students themselves used by Crosnoe (2007) . Further, the record of school absences, derived from school administrative data, is more reliable than the student self reports used by other authors (Daniels 2008). The survey also asked parents and students to predict how what level of education the student expects to achieve. A comparison of these two sources (parent and student reports) ensures a more precise measure of educational expectations. Second, ECLS-K has a relatively comprehensive measure of the determinants of obesity and achievement, including family background, nutrition, and physical activity. This set of covariates allows for models that reduce the biases from omitted variables. Third, the data set has repeated measures of behavioral problems, work habits, expectations, and truancy, which facilitate robustness checks.

[18] The ECLS-K refreshed its sample by adding 167 children in the fall of first grade (Wave III), and only collected 30% of the original sample during this wave of data collection.

Sample

To investigate the pathways that link obesity and academic achievement, I focus on a sample of 4,460 white children who have complete data on Item Response Theory (IRT)-scale test scores and obesity status at fifth and eighth grade.[19] The sub-sample with no missing values on any variables has 2,294 white children. Nearly 23 percent of these children are classified as obese (a BMI above the 95th percentile in both fifth and eighth grade). I use the sample of 2,294 children who have complete data on all covariates in the primary analysis, and supplement the primary results with an analysis of the imputed sample.

Dependent variables

The outcomes in this study include eighth-grade IRT-scale test scores in reading and math. The reading test measures students' skills in nine dimensions: letter recognition, beginning sounds, ending sounds, sight words, comprehension of words in context, literal inference, extrapolation, evaluation, and critical evaluation of literal works. The math test evaluates students' skills in number and shape, relative size, ordinal and sequence, addition and subtraction, division and multiplication, place value, rate and measurement, fractions, area, and volume. The reading IRT-scale scores have a mean of 171 points and a standard deviation of 27.6 points, and the

[19] I limit the analytic sample to white children because there are not enough African American and Hispanic children to allow effective matching.

math IRT-scale scores have a mean of 142 points and a standard deviation of 22 points. Distributions of both scores are slightly skewed toward the bottom. To facilitate a comparison across subjects, I use standardized scores in standard deviations as the unit of analysis.

Independent variables

The independent variable is a student's obesity status (respondents are categorized as obese if their BMI z-scores are 95th percentile in both fifth and eighth grade). The reference group includes students between the 5th and 75th percentiles on the BMI z-score distribution. As a sensitivity test, I use extreme obesity (BMI>97th percentile) as an independent variable in supplementary analyses.

Mediating variables

School Absence. Having a direct measure of school absences caused by obesity-related health problems would be ideal. However, the ECLS-K does not provide adequate data on the reasons for school absence to enable a clear distinction between obesity-related causes and other issues. I measure school absence more broadly using the available indicator in the ECLS-K data. Specifically, I measure school absence as the total number of absences for a student during fifth grade (i.e., the 2003-2004 school year). This information comes from the student records abstract form completed by school administer, in accordance with school attendance records. The response is a six-category variable, ranging from 0 to more than 10 days. I use the midpoint of each category to assign a value and construct a variable (0, 1, 2, 4, 8, 12).[20]

Behavioral Problems. Because past studies have emphasized the high prevalence rates and negative impacts of internalizing behavioral problems, I include internalizing behavioral problems that interfere with the learning processes or interactions in the classroom in the models. In the ECLS-K, teachers rated the internalizing problem behaviors of anxiety, loneliness, low self-esteem, and sadness on a scale of 1 (Never) to 4 (Very often). The reliability of the internalizing problem behavior variable is 0.77.

Reduced Parental Educational Expectation. ECLS-K asks parents to report what level of education they expect their children to achieve in a categorical fashion: less than high school, high school, some college, bachelor’s degree, master’s degree, doctoral degree, or professional degree. Because college education represents significant earnings prospects, I create a dummy variable for low educational expectations that indicates whether a parent expects his/her child to attain less than a bachelor’s degree.

Work Habits. To measure work habits, I use the approaches to learning suggested by other authors (Bodovski and Farkas 2008). The ECLS-K asks teachers to rate a student’s skills in five areas related to learning experience in the classroom

[20]The construction procedure is: 0=0; less than 1=1; 1 to less than 2=2; 2 to less than 5=4; 5 to less than 10=8; more than 10=12.

on a scale of 1 (never) to 4 (very often). The five areas are attentiveness, task persistence, eagerness to learn, learning independence, flexibility, and organization. The final work habits scale ranges from 1 to 4, representing the average rating a student received across the five items. Its split-half reliability is 0.91 (The ECLS-K User's Guide).

Background characteristics

To mitigate omitted variable bias, I control a number of covariates that could potentially influence both obesity status and academic achievement, and which occurred at or before fifth grade. Demographic variables include age, gender, and birth weight (in pounds). Weekly activity levels of students in third grade were measured in two ways using parent-report information: hours of TV viewing (i.e., TV, videotapes, or DVDs) per week, and number of days per week the student had 20 minutes of intensive exercise that caused rapid breathing, perspiration, and a rapid heartbeat. I used weekly soda consumption to gauge a student's level of nutrition in fifth grade. Family socioeconomic background in kindergarten included mothers' years of schooling, the percentage of college graduates among the jobholders in the fathers' occupation [21] and family income (log). Neighborhood atmosphere was measured by the parental assessment of how safe it is to play outside. Finally, I included public/private school attendance.

[21] This measures follows Hauser's (2008) strategy.

Missing values

An examination of the patterns of missing data in the covariates reveals that twelve of twenty covariates have missing values for at least some respondents, and the rates of missing values for four variables (reading scores in kindergarten, math scores in kindergarten, father's occupational status, and free lunch recipient status) account for the majority (around 75 percent) of missing data. Assuming data is missing at random, I fill in the missing values using imputation by chained equations implemented via the ICE procedure in STATA (Raghunathan et al. 2001; Van Buuren and Oudshoorn 2000). This imputation yields five imputed samples with 3,128 cases. The estimates represent the average effects across five samples using imputed data. I use the Rubin's correction method to calculate the associated standard errors (Rubin 1987). Compared to children in the case-complete sample, those with missing values are more likely to receive free lunch, live in unsafe neighborhoods, and have lower math scores in kindergarten.

Methods

The analysis consists of two parts. In the first part, I use a basic regression approach to assess the impact of the four mechanisms on reducing obesity penalties in reading and math test scores. In the second part, I use a regression-based decomposition approach to quantify the relative contributions of the four mechanisms in the reduction of the overall obesity penalties in reading and math test scores. I focus the analysis on obesity (BMI>95th percentile) and perform additional analyses using extreme obesity (BMI>97th percentile).

In the first part of analysis, I conduct ordinary least squares (OLS) regression analysis on four models. The first model tests whether being obese affects children's test scores in reading and math in eighth grade. Both reading and math test scores (Y_i) in eighth grade for individual i can be expressed as a function of obesity status (O_i) , a set of covariates (X_i'), and an error term (ε). The coefficient β_1 yields the estimated obesity penalty in test scores, net of family background, activity, nutrition, neighborhood, and school type.

$$Y_i = \alpha + \beta_1 O_i + \gamma_i X_i' + \varepsilon \qquad (1)$$

The second model tests whether obesity affects the school absence, behavioral problems, educational expectation, and work habits. In the second model, parental educational expectations (E_i) in fifth grade for individual i can be expressed as a function of obesity status (O_i) , a set of covariates (X_i'), and an error term (ε). This equation holds true for internalizing behavioral problems, school absence, and work habits. The coefficient δ_1 refers to the effect of obesity on low parental education, internalizing behavioral problems, school absence, and work habits, respectively.

$$E_i = \alpha + \delta_1 O_i + \gamma_i X_i' + \varepsilon \qquad (2)$$

The third model directly tests the unique explanatory power of the four mechanisms in mediating the relationship between obesity and academic achievement. In this model, test scores in eighth grade for individual i can be expressed as a function of obesity status (O_i) , low educational expectations (E_i), a set of covariates (X_i'), and an error term (ε). A comparison of the coefficients for obesity (β_1) in Models (1) and (3) can reveal the impact of low educational expectations in attenuating the obesity penalty in test scores. I conduct similar analyses for internalizing behavior problems, school absence, and work habits. Comparing the reduction of the obesity coefficient (β_1) across these regression models indicates the relative importance of these four mechanisms in producing the overall obesity penalty in test scores.

$$Y_{ij} = \alpha_j + \beta_{1j} O_{ij} + \beta_{2j} E_{ij} + \gamma_j' X_j' + \varepsilon_j \qquad j \in \{E, I, S, W\} \qquad (3)$$

The fourth model tests the collective explanatory power of the four mechanisms in accounting for the test score gaps between obese students and their thinner counterparts. A reduction in the obesity coefficient to insignificance from Model (1) to Model (4) will confirm the hypothesis that the estimated obesity penalty in test scores is due to low educational expectations (E_i) , internalizing behavior problems (I_i), school absence (S_i), and work habits (W_i). A comparison of the effect sizes ($\beta_{2,}$ $\beta_{3\,,}$ $\beta_{4\,,}$ β_5) between Models (3) and (4) further reveals the relationship among these four mechanisms.

$$Y_i = \alpha + \beta_1 O_i + \beta_2 E_i + \beta_3 I_i + \beta_4 S_i + \beta_5 W_i + \gamma' X' + \varepsilon \qquad (4)$$

An examination of changing regression coefficients will demonstrate the relative importance of each mechanism linking obesity and poor test scores. However, the observed obesity gaps in test scores can also be due to differences in the distributions of covariates between obese students and their normal-weight counterparts, in addition to differences in effect sizes. Thus, the second part of the analysis focuses on a regression-based decomposition approach to identify the relative contribution of each mechanism to the test scores gaps in eighth grade (Blinder 1973; Oaxaca 1973). I use the regression model to predict the mean test scores for obese and normal-weight students separately (subscripts o and n, respectively).

$$Y_j = \alpha_j + X_j' \beta_j + \varepsilon_j \qquad j \in \{o, n\} \qquad (5)$$

In this equation, X is a vector containing all four mechanism variables, covariates, and a constant, and β is the parameter to be estimated. When Δ represents the estimated score gap between obese and normal-weight students,

$$\Delta = \overline{Y_O} - \overline{Y_N} = \overline{X_O'}\widehat{\beta_O} - \overline{X_N'}\widehat{\beta_N}$$

$$= ((\overline{X_O} - \overline{X_N})' \widehat{\beta_N} + \overline{X_N}\left(\widehat{\beta_O} - \widehat{\beta_N}\right) + (\overline{X_O} - \overline{X_N})'\left(\widehat{\beta_O} - \widehat{\beta_N}\right) \qquad (6)$$

(Blinder 1973; Oaxaca 1973). The first component $((\overline{X_O} - \overline{X_N})' \widehat{\beta_N}$ represents the contribution of the differences in the *means* of the relevant mechanisms and covariates between obese and normal-weight students to the overall obesity penalty in test scores. Substantively, these terms indicate that how much of the obesity gaps in test scores are due to the differences in the days of school absence, the prevalence of reduced parental educational expectation, the severity of behavioral problems, degree of work habits, family socioeconomic background and reading ability at kindergarten. For example, if we assume that the effects of reduced educational expectations are essentially the same for obese students and their thinner counterparts, and the prevalence of reduced educational expectation is much higher for obese students than for normal-weight students, one should expect that difference in reduced educational expectation will contribute non-trivially to the obesity penalties in test scores. The second component $\overline{X_N}\left(\widehat{\beta_O} - \widehat{\beta_N}\right)$ represents the contribution of the differences in the *associations* of the relevant mechanisms and covariates to the overall obesity gaps in test scores. Substantively, these terms tell us that how much of the obesity gaps in test scores are due to difference in the relationship between students' characteristics and test scores. For example, one can assume that the chances of attending public school are equal for obese students and normal-weight students. If attending public school is associated with much lower test scores for obese students than for normal-weight students, one can expect that part of the obesity penalty in test scores can be attributable to the stronger relationship between attending public school and test scores. The third component $(\overline{X_O} - \overline{X_N})'\left(\widehat{\beta_O} - \widehat{\beta_N}\right)$ represents the interaction between the means and associations. Analysis of each of these components will highlight the variable influence of the determinants in accounting for the overall obesity gaps.

Despite the attempts to reduce bias, I am cautious about making causal inferences about the estimated obesity penalties for test scores. Although I control for a number of factors, there may be unobserved variables that simultaneously determine both obesity and reading scores. For example, school budget deficits may limit students' access to physical activity, and also restrict their access to high-quality teachers. In this case, poor achievement among obese students cannot be attributed to only weight status. Further, I am aware the possibility of reverse causality, that is, obesity leads to more TV viewing and less activity. I do not estimating models with fixed effects or through differences, as another strategy to wipe out effects of endogenous covariates. Further, I do not have the tools to adjust for selection with propensity score matching and decompose the adjusted effects simultaneously.

Results

Descriptive results

As shown in Table 5, obese students differ significantly from their normal-weight peers with regard to both academic achievement and the mechanisms leading to low achievement. First, obese children, on average, score significantly lower on eighth-grade reading and math tests than their normal-weight counterparts. The obesity difference in reading is 0.36 standard deviations (9.67 points); the difference in math is 0.30 standard deviations.

Second, the most noticeable finding is that obese children have poor outcomes on non-cognitive measures. These children have 0.31 more days of school absence than their normal-weight counterparts. Their teachers report a higher degree of internalizing behavioral problems (0.19) and poorer work habits (-0.22). Their parents are 20 percent more likely to expect that these students will not gain education beyond high school.

Third, there are many preexisting differences in health behaviors between obese children and their normal-weight counterparts. In a typical week, obese children tend to drink more cans of soda, spend more hours watching TV and playing video games, and spend fewer hours in intensive exercise. In addition, obese children are more likely to come from disadvantaged families. Their family incomes are lower, their mothers on average complete one less year of schooling, their fathers work in occupations that have fewer college graduates, and they tend to live in unsafe neighborhoods.

Does obesity depress academic achievement?

To identify the obesity gap in academic achievement net of family background, I regress the test scores on obesity status, controlling for birth weight, health behaviors, and family socioeconomic status. Results from Column 1 of Table 7 and Table 8 show that obesity has a negative impact on both reading and math scores in eighth grade. Net of controls, being obese is associated with a decrease of 0.096 standard deviations in reading and 0.077 standard deviations in math. These negative effects are considerable, equivalent to the effects of two years less of maternal schooling. However, these estimates may not represent the causal impacts of obesity on test scores because unobserved variables may simultaneously determine both obesity and reading scores. For example, school budget deficits may limit students' access to physical activity, and also restrict their access to high-quality teachers.

Does excessive weight hurt non-cognitive skills?

Descriptive analysis has shown that obese children have worse outcomes on non-cognitive measures, and are more likely to come from disadvantaged families. Do these differences in non-cognitive traits remain after controlling for preexisting family conditions? I use logistic regression and OLS regression models to predict the differences in the non-cognitive traits net of family background and birth conditions. The coefficient for binary outcome in the logistic regression represents the marginal effect (dy/dx) in percentage points. The reference groups are normal-weight children.

The most important finding in Table 6 is that compared to normal-weight peers, obese children tend to have poorer work habits. The effect size (-0.119) of obesity is equivalent to a 4 percent reduction in the mean score of the work habits indicator. If obese children have poor work habits in the learning process, it is reasonable to expect that they may fall behind in school performance.

Other results of Table 6 confirm earlier findings. In general, obese children tend to have more internalizing behavioral problems, more school absences, and a lower degree of parental expectations, net of family socioeconomic status. For example, the estimated rate of low parental expectations is 15.4 percentage points higher for obese children than for normal-weight children. Additionally, obese children, on average, score 0.111 points higher on the scale of internalizing behavioral problems, and miss 0.233 more days of school. Thus, the data reveal significant differences in work habits, behavioral problems, school absence, and parental expectations between obese and normal-weight children. The higher incidence of low parental expectations, internalizing behavioral problems, and school absences is consistent with prior findings (Daniels 2008; Falkner et al. 2001; Strauss 2000). Because parental expectations continue to influence subsequent investment, and behavioral problems disturb concentration, it is reasonable to expect that such disadvantages will translate into lower academic performance.

Do non-cognitive skills explain the obesity gaps in test scores?

The results in Tables 5 and 6 demonstrate that obese children achieve lower scores on standardized test scores than their normal-weight peers, and they also tend to have poorer work habits, as well as a higher degree of low parental expectations, school absences and behavioral problems. Can the obesity penalties in test scores be attributed to the differences in these non-cognitive measures? If so, which measure is the most important mechanism explaining obesity difference? I hypothesize that all four mediating factors will contribute to obesity differences, but that work habits are the most important variable. To test these hypotheses, I use a step-wise regression strategy to examine the relative importance of each mechanism. I expect that the associations between obesity and test scores will be attenuated as I add each mediating factor to the regression equation, net of family socioeconomic status. Table 7 compares the explanatory powers of these four mechanisms to predict obesity penalties for reading test scores.

Reduced Educational Expectation

On average, parents of obese students have lower levels of educational expectations than those of normal-weight students. Do reduced educational expectations disturb the academic achievement of obese students? As shown in Columns 2 of Table 7, low levels of educational expectations play a somewhat significant role in explaining why obese children fall behind in reading. The obesity penalty in reading scores moderately declines roughly 10 percent when low educational expectation is added to the model. Furthermore, paralleled with prior studies (Fan and Chen 2001), reduced educational expectation remains powerful in predicting academic achievement, as students tend to score 0.324 standard deviations lower in reading when their parents move from high expectation to low expectation. This effect persists after controlling for behavioral problems, school absence and poor work habits. In summary, reduced educational expectation is a non-trivial pathway linking obesity with poor reading test scores. These findings provide support to the weight stigma model, indicating that obesity leads to greater degree of weight stigma, which in turn, disrupts students' academic performance.

Behavioral Problems

Results in Table 7 show interesting role of the internalizing behavioral problems in mediating the effect of obesity on poor reading test scores. A high level of internalizing behavioral problems explains one-quarter of the obesity gap in reading scores (Column 3). The significant effect of behavioral problems among eighth graders parallels finding from previous studies of adolescents (Crosnoe 2007). However, the mediating effects of internalizing behavioral problems reduce to insignificance when poor work habits are added to the model. This change indicates that behavioral problems are a weak pathway. It is likely that students with internalizing behavioral problems may develop poor work habits which disrupt their acquisition of knowledge.

School Absence

The data in the Column 4 of Table 7 suggest that a higher rate of school absence among obese children, on average, explains one-tenth of the negative effect of obesity gap in reading scores. This result is consistent with prior findings (Daniels 2008). Yet, school absence itself is only weakly associated with reading achievement when reduced parental education and work habits are controlled. In sum, while obese children miss more days of school, this link is weak relative to other mechanisms.

Work Habits

Results from Columns 2-6 of Table 7 confirm the hypothesis that work habits are the most important mechanism linking obesity and poor academic achievement. The first evidence is that the largest attenuation in the association between obesity and reading scores comes when work habits are added in the step-wise regression process. After controlling for differences in work habits, the effect of obesity is reduced by almost half (compares Columns 1 and 5), in striking contrast to the 10 percent reduction when parental expectations (compare Columns 2 and 5) are added. The increasing value of the adjusted R^2 also suggests that work habits explain more variation in reading scores than other factors.

Second, work habits remain a strong explanatory factor when school absence, reduced parental expectation and behavioral problems are included in the model (Column 6 of Table 7). A one-point increase in the work habits is associated with a 0.345 standard deviation increase in reading scores. They are significant predictor when controlling for educational expectations. Finally, work habits explain a portion of the effects of the other three mechanisms (Column 6 of Table 7). Notably, the negative impact of internalizing behavioral problems drops from 0.185 to 0.039 standard deviations and is no longer statistically significant when work habits are controlled. The associations of low paternal expectations and school absence with reading scores are also reduced by more than 20 percent when work habits are included in the model. Thus, these findings support the second hypothesis that work habits are the most important mediating factor explaining the obesity gap in reading scores.

The results in Column 6 clearly confirm the first hypothesis that a combination of the four mechanisms explains the obesity differences in reading in eighth grade. The effect of obesity on reading is no longer statistically significant, and the obesity penalty declines from 0.09 standard deviations to 0.041 standard deviations, when parental educational expectations, behavioral problems, school absence, and work habits are all controlled. Notably, low expectations and work habits have strong impacts on reading achievement. Taken together, these results provide evidence that the work habits model and the weight stigma model explain the majority of the obesity penalty in reading.

How do non-cognitive skills mediate the effect of obesity on math scores?

To test whether the relative contributions of the various mechanisms differ by subject, I perform a similar analysis for math and report the results in Table 8. The results yield a similar conclusion as the findings for reading. In general, work habits, parental educational expectations, internalizing behavioral problems, and school absence collectively explain the obesity penalty in math. Work habits remain the most important mediating factor. Despite these similarities, the effects of school absence and internalizing behavioral problems operate differently for math and reading. Unlike their insignificant impact on reading, both factors remain statistically significant factor in predicting math scores even when behavioral problems, work habits, and parental expectations are included in the model. One possible explanation is related to the different study strategies required to succeed at reading and math tests. Fulfillment of the most difficult tasks on a math test (fractions, area, and volume) requires more guidance and practice in the classroom. Thus, frequent school absences not only disturb the learning process, but also exacerbate the effects of work habits.

In sum, empirical investigation reveals the significant role of work habits and parental expectations in explaining the obesity penalties in reading and math. Work habits alone could offset the negative impact obesity, net of other factors.

Relative importance of the four mechanisms from decomposition analysis

To assess the relative contributions of various mechanisms in explaining the overall obesity penalties, I perform regression analysis for obese and normal-weight students separately (Table 9) and conduct regression-based decomposition. (Blinder 1973; Oaxaca 1973). In the decomposition process, the observed obesity gaps consist of three parts. The first component $((\overline{X_O} - \overline{X_N})' \widehat{\beta_N}$ or "means" indicates that how much of the obesity gaps in test scores are due to the differences in the characteristics of obese students and those of normal-weight students, for example, more days of school absence, lower levels of educational expectation, severer behavioral problems, or poorer work habits among obese students. The second component $\overline{X_N}\left(\widehat{\beta_O} - \widehat{\beta_N}\right)$ or "associations" represents tell us that how much of the obesity gaps in test scores are due to difference in the relationship between students' characteristics and test scores, for example, stronger effects of birth weight on test scores for normal-weight students than for obese students. The third component $(\overline{X_O} - \overline{X_N})'(\widehat{\beta_O} - \widehat{\beta_N})$ represents the interaction between the means and associations. The substantive meanings of the first two components are clear in the following two examples. First, if we assume that the effects of reduced educational expectations are essentially the same for obese students and their thinner counterparts, and the prevalence of reduced educational expectation is much higher for obese students than for normal-weight students, one should expect that difference in reduced educational expectation will contribute non-trivially to the obesity penalties in test scores. Second, one can assume that the chances of attending public school are equal for obese students and normal-weight students. If attending public school is associated with much lower test scores for obese students than for normal-weight students, one can expect that part of the obesity penalty in test scores can be attributable to the stronger relationship between attending public school and test scores.

As shown in Table 5, obese students differ significantly from their thinner counterparts in terms of school attendance, educational expectation, behavioral problems, work habits, birth weight, family socioeconomic background, neighborhood safety, school type and reading ability at kindergarten. Yet, results in Table 9 show that the associations of these characteristics with reading and math test scores are similar between obese students and their thinner counterparts. Among thirteen predictors, only three of them have different effect sizes and effect directions in predicting reading and math test scores. For example, the effects of school absence and birth weight on reading test scores are weaker for obese students than for normal-weight students. Given these patterns, I expect that the majority of the observed obesity penalty will attributable to differences in population characteristics. Table 10 displays the contributions of the four pathways to the obesity penalty both as an absolute number and as proportion of the total test scores. Positive values in the “test scores (SD)” column represent differences in composition or association contribute to the observed obesity gaps in test scores, while negative values indicate that differences offset the obesity gaps.

As expected, the differences in means account for the majority of the observed differences in reading scores between obese and normal-weight children, while the contribution of the differences in effect sizes is trivial. In other words, obese children would attain parity in reading scores if they had the same means for the covariates as their normal-weight counterparts. For example, poorer work habits among obese children translate to a 0.06 standard deviation reduction in reading and math scores.

Second, a combination of the four mechanisms accounts for roughly half of the overall obesity differences in reading scores. Summing the contributions of work habits, parental expectations, behavioral problems, and school absence yields a difference of 0.109 standard deviations in reading scores between obese and normal-weight children. This combined contribution indicates that the obesity penalty in reading would have shrunk from -0.237 to -0.137 standard deviations, had obese children shared the same characteristics in the distribution as their normal-weight counterparts. Similarly, the four mechanisms combined account for two-fifth of the observed obesity differences in math.

Third, the decomposition results further confirm that, of the four mechanisms evaluated, work habits remains the largest contributor to the observed differences in reading scores between obese and normal-weight children. Results in Table 10 show that work habits contribute to a 0.068 standard deviation reduction in reading or one-quarter of the observed obesity differences; this contribution is comparable to that of school readiness in kindergarten (measured by kindergarten reading scores). In the case of math, work habits account for about one-third of the obesity gap. Parental expectations make the second-largest contribution to the observed differences. In contrast, the roles of behavioral problems and school absence are minimal. Thus, the decomposition results further confirm the two hypotheses.

Finally, the decomposition analysis also highlights the important roles played by school readiness and family socioeconomic status in accounting for obesity differences in test scores. Results in Table 10 show that roughly one-third of the obesity gap in reading is due to lower test scores in kindergarten among obese students, while another one-third is due to their more disadvantaged family background. In the case of math, kindergarten scores account for two-fifths of the overall obesity penalty. These findings are not new, but they quantify the effect size of school readiness and family socioeconomic background.

Testing the Sensitivity of Regression and Decomposition Results

To test the sensitivity of the regression and decomposition results, I perform three sets of auxiliary analyses. The first two sets of analyses use alternative measures of obesity and the mediating factors. The third analysis uses the case-complete sample.

First, I repeat the original analysis for extremely heavy children whose BMI z-scores are at or above the 97^{th} percentile. As the degree of obesity increases, I expect that the obesity difference will become larger with respect to test scores, work habits, parental educational expectations, internalizing behavioral problems, and school absence, but the relative importance of the various mechanisms will remain the same as for obese children. The estimation results for extremely obese children generally confirm these expectations (results not shown). Notably, low parental educational expectations make a slightly larger contribution (4 percentage points) to the explanation of obesity penalties in test scores for extreme obese children (BMI$\geq 97^{th}$ percentile) than for obese children (BMI$\geq 95^{th}$ percentile). Work habits remain the largest contributing factor. These findings underscore the crucial role that low educational expectations have played in establishing the achievement gap at eighth grade.

As a second sensitivity test, I use measures of the mediating factors from eighth grade to test the robustness of estimates. Of the four mechanisms examined, parental educational expectations are the only one that was measured in both fifth and eighth grade. I construct measures of behavioral problems and work habits from parental reports in eighth grade.[22,23] The number of school absences is obtained from teachers' reports, instead of school administration data. Not surprisingly, the obesity gap in parental expectations remains the same, while the estimated differences in work habits, internalizing behavioral problems, and school absence between obese and normal-weight children are smaller when using the constructed measures in eighth grade. These smaller differences in the variables representing key mechanisms also translate into weaker effects in explaining the observed obesity penalties in test scores. For instance, the inclusion of work habits reduced the obesity penalty in reading by only 10 percent, in striking contrast to the 60 percent reduction when using teacher-evaluated measures. In addition, half of the obesity penalty in reading remains after controlling all four mechanisms. These weaker effects further demonstrate that work habits reflect a student's traits beyond attention level, and

[22] Ideally, gender-specific analysis can shed light on the pathways that produce the obesity penalty in test scores. However, the small size of the case-complete sample does not allow enough statistical power to conduct gender-specific analysis.

[23] Because the ECLS-K stopped asking teachers to evaluate students' internalizing behavioral problems and work habits, I construct two rough measures from parental responses to questions about a child's mental well-being. The constructed measure of internalizing behavioral problems includes loneliness, worries, nervousness, fear, and depression, but lacks low self-esteem. The measure of work habits consists of prudence, a long attention span, and being considerate, but misses eagerness to learn, flexibility, and persistence. In addition to the inclusion of different items, the reliabilities of these two new measures constructed from parental responses are far less than the reliabilities of the original measures constructed from teacher evaluations. Also, the number of school absences is obtained from the teacher's report, instead of school administrative data. Thus, I expect that the newly constructed internalizing behavioral problems, work habits and school absence variables will yield slightly different results because they do not fully capture the traits reflected in variables based on teachers' evaluations.

missing other dimensions of the measure will likely weaken the power of work habits.[24]

Finally, I perform similar regression and decomposition analyses using the case-complete sample and report the results in the appendix. As expected, the analyses of the case-complete sample yield similar conclusions as those reported in the imputed sample. These findings reveal significant differences in work habits, parental educational expectations, and internalizing behavioral problems between obese students and their normal-weight counterparts (Table A4). Despite smaller effect sizes, step-wise regression results show that these four factors collectively mediate the effects of obesity on test scores, and work habits remain the most important mediating factor (Table A5 and Table A6). Additionally, findings from the decomposition analysis reveal essentially the same contributions of work habits and parental educational expectations in case-complete sample as those in the imputed sample (Table A8). Thus, these findings suggest that missing values do not distort the main conclusions about the relative contributions of four pathways.

Discussion and conclusion

[24] An alternative way of testing the sensitivity of internalizing behavioral problems and work habits would be to use similar measures based on teacher evaluations in third grade. Although the measure remains the same, the results are hard to interpret because these two traits affect a child's probability of being obese in fifth grade. Results show larger obesity differences in work habits and the predominant role of this difference in explaining obesity penalties in test scores. The observed reading gap between obese and normal-weight children almost vanishes after I control work habits in the regression. The same is true for the math gap. Thus, these results confirm earlier finding that work habits are the most important mechanism linking obesity and underachievement.

Childhood obesity is associated with poorer academic achievement (Averett and Stifel 2010; Crosnoe 2007; Ding et al. 2009). Studying the mechanisms underlying this effect is particularly important to improve the well-being of obese students in the context of the current obesity epidemic. Rooted in the cultural capital framework, this study examines the relative importance of work habits, behavioral problems, parental educational expectations, and school absence in accounting for the achievement gap between obese children and their thinner counterparts. Using a nationally representative sample of children from the Early Childhood Longitudinal Study, I show that poor work habits and reduced parental expectations account for about half of the obesity penalties in reading and math, while the influence of behavioral problems and school absence is minimal. Decomposition results further demonstrate that the majority of the observed differences are due to differences in population characteristics between obese children and their thinner peers. These findings not only support the theory that weight stigma is a source of underachievement, but also confirm the important role of non-cognitive measures in boosting cognitive skills during childhood. The results suggest that in addition to reducing stigma, fostering good work habits may compensate for the disadvantaged social position of obese youth.

This study extends current explorations of the pathways linking obesity and academic achievement by incorporating the non-cognitive skill perspective. The current dialogue about the obesity penalty in test scores focuses on behavioral problems, low parental educational expectations, and school absence. However, these pathways explain only part of the obesity gap, and exactly how they work remains unclear. Introducing the work habits perspective into the current dialogue not only highlights a crucial pathway overlooked by past studies, but also helps to better explain the role of behavioral problems, reduced educational expectations and school absence. Work habits are the implementation of educational expectations, and they focus on both the quality of school participation and the quantity of school absences. Work habits also mediate the negative impact of behavioral problems on poor test scores. Empirical findings show that controlling work habits attenuate the effect of educational expectations by 20 percent, decrease the effect of behavioral problems to insignificance, and substantially reduce the effect of school absence. Thus, the work habits perspective goes beyond past studies by emphasizing the attention, eagerness, and strategies that are crucial traits in an effective learning process. Additionally, because these traits are malleable and open to change via intervention, incorporating the work habits perspective is of practical importance for boosting the academic achievement of obese children.

Second, to my knowledge, this study is the first comprehensive empirical study to assess the relative importance of these four mechanisms through both regression and decomposition analysis. Most past studies, using primarily regression techniques, have focused on behavioral problems and health-related school absences. None of these studies have examined the role of parental educational expectations and work habits, nor have they used decomposition techniques to quantify the relative contributions of various mechanisms. This study extends the literature by identifying and quantifying the relative contributions of all four mechanisms. These findings speak to a broader conclusion that non-cognitive variables are key mediators of academic achievement for obese children. Although the least square regression and decomposition analyses are insufficient to prove the causal pathways, I have included a relatively comprehensive set of covariates in the regression and decomposition to minimize biases related to observed variables which were not available in past studies. In particular, controlling diet quality, neighborhood and school characteristics enable me to identify the unique effects of work habits and educational expectations.

A few studies have shown that behavioral problems and school absence account for the reduced educational attainment of obese students (Crosnoe 2007; Sigfusdottir, Kristjansson and Allegrante 2007). This study moves beyond these findings by revealing that a portion of the effects of behavioral problems and school absence operate through work habits. For example, although behavioral problems are a strong predictor of academic achievement, adding work habits to the model decreased the variable’s effect to insignificance and reduced the effect by 75 percent. One possible explanation is that anxiety, sadness, and low self-esteem may translate into passive learning practices, such as a lack of attention, eagerness, and flexibility. Thus, these findings do not repudiate the role of behavioral problems; rather, they suggest that part of the way in which behavioral problems and school absence influence the academic achievement of obese children is through poor work habits.

Additionally, two studies have shown that controlling diet quality and physical activity eliminates the negative impacts of obesity on grade point average or grade level (Huang, Goran and Spruijt-Metz 2006; Wang and Veugelers 2008) (Wang and Veugelers 2008). This study extends the current literature by revealing the contributions of diet quality to the overall obesity gaps after controlling other important covariates such as non-cognitive measures, and school and neighborhood characteristics. In this study, the significant role of work habits and parental educational expectations prevail, but the effects of soda consumption decline. These changes indicate that unhealthy diet may disrupt attention, eagerness, and flexibility in the learning process. Thus, the effects of work habits and parental expectations are more important than the effects of diet quality.

These findings underscore the importance of parental investment in fostering good work habits. Active parental involvement in learning may be one of several ways to improve the academic achievement of obese students. For example, parents can teach their children a strong work ethic by working on school projects together, praising them as hard workers when they make persistent efforts, or encouraging them to take challenges and persevere (Rimm and Rimm 2004). Parental involvement can also enrich their children's knowledge by teaching them information before they learn it in school, or by helping them research information on the internet, at the library, or in museums (Bodovski and Farkas 2008). Additionally, parents can be role models for their children by maintaining a positive attitude toward work.

The findings in this study indicate the need for future research on the mechanisms explaining the obesity penalty in academic achievement. First, the regression-based study of mechanisms is insufficient to establish a causal link between obesity, work habits, and poor academic achievement. Future research should take advantage of recent developments in causal mechanism research to advance the scholarly understanding of this complex relationship (Imai et al. 2011). Second, given racial and ethnic variations in the degree of weight stigma, it is crucial to compare the mediating effects of work habits and parental educational expectations among African American and Hispanic students. Third, the persistent effect of parental educational expectations calls for more attention on parental investment. Future studies should identify particular types of parental investment that benefit obese students. Fourth, although overall school absence is a weak mediating factor in this study, obesity-related school truancy may make a large difference among adolescence. Further study is very much needed to explore the relationship between obesity and extensive school absences.

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Table 5. Summary statistics of obese and normal-weight students for the imputed sample

	Mean		Differences	p-values
	Obese	Normal-Weight		
Outcomes				
Reading	0.316	0.077	0.239	***
	(1.059)	(0.977)		
Math	0.238	0.103	0.136	***
	(1.000)	(0.964)		
Pathways				
Reduced parental educational expectation	0.321	0.200	0.121	***
	(0.467)	(0.400)		
Internalizing behavioral problems	1.725	1.579	0.146	***
	(0.563)	(0.519)		
School Absence	4.217	3.974	0.243	***
	(1.745)	(1.615)		
Approaches to learning	2.937	3.145	-0.208	***
	(0.662)	(0.660)		
Controls				
Girl	0.415	0.493	-0.078	***
	(0.493)	(0.500)		
Age	11.054	11.064	-0.010	
	(0.359)	(0.351)		
Birth weight	7.606	7.354	0.253	***
	(1.338)	(1.252)		
Family Income (log)	10.327	10.720	-0.393	***
	(0.863)	(0.892)		
Mother's Years of Schooling	12.524	13.853	-1.329	***
	(3.102)	(2.975)		
Father's Occupation (% college graduates)	0.184	0.275	-0.092	***
	(0.224)	(0.287)		
Neighborhood Unsafe to Play	0.268	0.194	0.073	**
	(0.443)	(0.396)		
Public School	0.915	0.853	0.062	***
	(0.279)	(0.355)		
Reading IRT Scale Score at Kindergarten	27.464	30.564	-3.101	***

	(8.784)	(10.046)
N	1,113	3,327

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE: * p<0.05; ** p<0.01; ***p<0.001.

Table 6.Estimated differences in mechanisms between obese and normal-weight students from the imputed sample

	Reduced Educational Expectation	Internalizing Behavioral Problems	School Absence	Approaches to Learning
Obesity	0.154*	0.111***	0.233***	-0.119***
	(0.090)	(0.021)	(0.068)	(0.024)
Girl	-0.214***	-0.078***	-0.002	0.368***
	(0.080)	(0.016)	(0.068)	(0.019)
Age	0.590***	-0.043*	0.170**	0.042
	(0.114)	(0.024)	(0.083)	(0.028)
Birth weight	0.017	-0.015**	0.033	0.021***
	(0.030)	(0.006)	(0.026)	(0.008)
Family Income (log)	-0.227***	-0.037***	-0.062*	0.076***
	(0.054)	(0.012)	(0.037)	(0.014)
Mother's Years of Schooling	-0.085***	0.002	-0.001	0.002
	(0.015)	(0.003)	(0.013)	(0.004)
Father's Occupation (% college graduates)	-1.273***	-0.015	0.025	0.035
	(0.219)	(0.033)	(0.103)	(0.042)
Neighborhood Unsafe to Play	-0.103	0.041*	-0.156**	-0.062**
	(0.101)	(0.022)	(0.070)	(0.025)
Public School	0.441***	0.025	0.095	0.007
	(0.123)	(0.019)	(0.065)	(0.024)
Reading IRT Scale Score at Kindergarten	-0.057***	-0.004***	-0.008**	0.010***
	(0.007)	(0.001)	(0.003)	(0.001)
Constant	-2.841**	2.669***	2.673***	1.220***
	(1.382)	(0.293)	(1.026)	(0.348)
N	4460	4460	4460	4460
Adjusted R^2		0.040	0.012	0.155

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006) imputed sample
NOTE: [a] I use linear regression to estimate the effect of obesity on work habit, internalizing behavioral problem and school absence, and logistic regression to estimate that on low parental educational expectation. The coefficients of obese represent percentage points (dy/dx) associated with moving from normal weight to obesity. * p<0.05; ** p<0.01; ***p<0.001.
[b] Control variables include gender, age, birth weight, family income (log), maternal education, paternal occupation, unsafe neighborhood and attending public school.

Table 7.Estimated relative importance of four mechanisms to explain the obesity penalty in reading scores from regression for the imputed sample

	Models				
	1	2	3	4	5
Obesity[a]	-0.096***	-0.087***	-0.067**	-0.064**	-0.041
	(0.032)	(0.031)	(0.031)	(0.031)	(0.030)
Reduced parental educational expectation		-0.324***	-0.299***	-0.294***	-0.245***
		(0.037)	(0.036)	(0.036)	(0.036)
Internalizing behavioral problems			-0.185***	-0.180***	-0.039
			(0.025)	(0.025)	(0.027)
School Absence				-0.019**	-0.012
				(0.009)	(0.009)
Approaches to learning					0.345***
					(0.022)
Girl	0.145***	0.133***	0.119***	0.120***	0.005
	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
Age	-0.035	-0.009	-0.019	-0.016	-0.029
	(0.038)	(0.038)	(0.038)	(0.038)	(0.036)
Birth weight	0.037***	0.037***	0.034***	0.035***	0.030***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Family Income (log)	0.157***	0.143***	0.137***	0.136***	0.118***
	(0.021)	(0.020)	(0.020)	(0.020)	(0.019)
Mother's Years of Schooling	0.058***	0.052***	0.053***	0.053***	0.053***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Father's Occupation (% college graduates)	0.105*	0.066	0.067	0.068	0.063
	(0.054)	(0.053)	(0.053)	(0.053)	(0.048)
Neighborhood Unsafe to Play	-0.135***	-0.138***	-0.130***	-0.133***	-0.116***
	(0.035)	(0.034)	(0.034)	(0.034)	(0.033)
Public School	-0.174***	-0.157***	-0.154***	-0.152***	-0.162***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.026)
Reading IRT Scale Score at Kindergarten	0.031***	0.029***	0.028***	0.028***	0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-3.155***	-3.096***	-2.608***	-2.571***	-3.397***
	(0.485)	(0.475)	(0.481)	(0.483)	(0.468)

N	4460	4460	4460	4460	4460
Adjusted R^2	0.320	0.337	0.346	0.347	0.385

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE:
[a] I use linear regression to estimate the effect of obesity and four mechanisms on reading scores. * p<0.05; ** p<0.01; ***p<0.001.
[b] Control variables include gender, age, birth weight, cans of soda consumed, days of intensive exercise, hours of TV viewing , family income (log), maternal education, paternal occupation, unsafe neighborhood and attending public school.

Table 8.Estimated relative importance of four mechanisms to explain the obesity penalty in math scores from regression for the imputed sample

	Models				
	1	2	3	4	5
Obesity	-0.077**	-0.069**	-0.045	-0.037	-0.014
	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)
Reduced parental educational expectation		-0.315***	-0.284***	-0.275***	-0.224***
		(0.037)	(0.037)	(0.037)	(0.035)
Internalizing behavioral problems			-0.222***	-0.212***	-0.067**
			(0.026)	(0.026)	(0.027)
School Absence				-0.041***	-0.034***
				(0.008)	(0.008)
Approaches to learning					0.353***
					(0.023)
Girl	-0.151***	-0.163***	-0.179***	-0.178***	-0.295***
	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
Age	-0.038	-0.013	-0.025	-0.019	-0.032
	(0.038)	(0.038)	(0.038)	(0.038)	(0.036)
Birth weight	0.047***	0.047***	0.044***	0.045***	0.040***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Family Income (log)	0.163***	0.149***	0.142***	0.140***	0.121***
	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)
Mother's Years of Schooling	0.050***	0.045***	0.046***	0.046***	0.046***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Father's Occupation (% college graduates)	0.100*	0.062	0.063	0.065	0.061
	(0.056)	(0.055)	(0.054)	(0.054)	(0.050)
Neighborhood Unsafe to Play	-0.109***	-0.112***	-0.103***	-0.110***	-0.092***
	(0.035)	(0.035)	(0.035)	(0.034)	(0.033)
Public School	-0.045	-0.028	-0.024	-0.021	-0.031
	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)

Reading IRT Scale Score at Kindergarten	0.031***	0.029***	0.029***	0.028***	0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-3.096***	-3.039***	-2.453***	-2.371***	-3.216***
	(0.490)	(0.479)	(0.481)	(0.482)	(0.465)
N	4460	4460	4460	4460	4460
Adjusted R^2	0.288	0.304	0.318	0.322	0.362

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE:
[a] I use linear regression to estimate the effect of obesity and four mechanisms on reading scores.
[b] Control variables include gender, age, birth weight, cans of soda consumed, days of intensive exercise, hours of TV viewing , family income (log), maternal education, paternal occupation, unsafe neighborhood and attending public school.

Table 9.Weight-specific effects of pathways on test scores for the imputed sample

	Reading		Math	
VARIABLES	Obese	Normal-weight	Obese	Normal-weight
Reduced educational expectations	-0.294***	-0.207***	-0.233***	-0.211***
	(0.066)	(0.041)	(0.063)	(0.043)
Internalizing behavioral problems	-0.015	-0.026	-0.044	-0.059*
	(0.048)	(0.031)	(0.051)	(0.034)
School absence	0.007	-0.017**	-0.026	-0.038***
	(0.018)	(0.008)	(0.016)	(0.009)
Approaches to learning	0.356***	0.350***	0.362***	0.358***
	(0.046)	(0.025)	(0.045)	(0.028)
Girl	-0.080	0.043	-0.303***	-0.287***
	(0.054)	(0.028)	(0.053)	(0.028)
Age	-0.063	-0.025	-0.008	-0.049
	(0.080)	(0.040)	(0.075)	(0.040)
Birth weight	-0.006	0.047***	0.016	0.052***
	(0.019)	(0.012)	(0.019)	(0.012)
Family Income (log)	0.119***	0.119***	0.105***	0.131***
	(0.040)	(0.022)	(0.040)	(0.023)
Mother's Years of Schooling	0.038***	0.057***	0.047***	0.044***
	(0.010)	(0.006)	(0.009)	(0.006)
Father's Occupation (% college graduates)	0.215*	0.035	0.077	0.052
	(0.114)	(0.052)	(0.116)	(0.055)
Neighborhood Unsafe to Play	-0.129**	-0.114***	-0.045	-0.116***
	(0.062)	(0.038)	(0.062)	(0.039)
Public School	-0.259***	-0.136***	-0.166***	0.002
	(0.066)	(0.029)	(0.063)	(0.030)
Reading IRT Scale Score at Kindergarten	0.034***	0.024***	0.029***	0.025***
	(0.004)	(0.002)	(0.004)	(0.002)
Constant	-2.883***	-3.639***	-3.238***	-3.209***
	(0.992)	(0.511)	(0.947)	(0.528)
N	1133	3327	1133	3327
Adjusted R^2	0.330	0.389	0.310	0.362

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE: * p<0.05; ** p<0.01; ***p<0.001.

Table 10.Estimated contributions of four mechanisms to the observed differences in test scores between obese and normal-weight students for the imputed sample.

		Reading		Math	
		Test scores (SD)	Proportion total differences	Test scores (SD)	Proportion total differences
Differential					
	Normal-weight	0.297		0.288	
	Obesity	0.015		0.082	
	Difference	0.281		0.206	
Endowments					
	Low educational expectation	0.042	0.150	0.032	0.158
	Internalizing behavior problems	0.010	0.036	0.014	0.070
	School absence	-0.007	-0.026	0.006	0.030
	Work habits	0.068	0.241	0.065	0.315
	Girl	0.001	0.002	-0.026	-0.128
	Age	0.001	0.003	0.001	0.002
	Birth weight	0.011	0.040	0.002	0.009
	Family income (log)	0.019	0.069	0.011	0.054
	Maternal education	0.006	0.020	0.043	0.211
	Paternal occupation	0.026	0.091	0.011	0.051
	Unsafe neighborhood	0.000	-0.001	-0.004	-0.018
	Public school	0.020	0.070	0.009	0.043
	Reading ability at kindergarten	0.080	0.284	0.067	0.327
	Total	0.275	0.978	0.232	1.124
Coefficients					
	Low educational expectation	0.045	0.160	0.008	0.041
	Internalizing behavior problems	-0.022	-0.077	-0.017	-0.084
	School absence	-0.158	-0.562	-0.109	-0.528
	Work habits	-0.105	-0.373	-0.052	-0.253
	Girl	0.006	0.023	-0.029	-0.142
	Age	1.324	4.712	0.149	0.721

	Birth weight	0.639	2.275	0.439	2.131
	Family income (log)	0.163	0.578	0.535	2.599
	Maternal education	0.635	2.260	-0.014	-0.070
	Paternal occupation	-0.039	-0.139	-0.008	-0.040
	Unsafe neighborhood	-0.007	-0.025	-0.037	-0.182
	Public school	0.111	0.396	0.107	0.517
	Reading ability at kindergarten	-0.223	-0.793	-0.070	-0.340
	Constant	-2.330	-8.292	-0.902	-4.379
	Total	0.041	0.145	-0.002	-0.008
Interaction					
	Low educational expectation	-0.017	-0.062	-0.003	-0.016
	Internalizing behavior problems	0.002	0.008	0.002	0.009
	School absence	0.013	0.047	0.009	0.043
	Work habits	-0.007	-0.027	-0.004	-0.018
	Girl	0.002	0.007	-0.010	-0.046
	Age	-0.001	-0.003	0.000	-0.001
	Birth weight	-0.026	-0.091	-0.017	-0.085
	Family income (log)	0.005	0.017	0.016	0.077
	Maternal education	0.045	0.160	-0.001	-0.006
	Paternal occupation	-0.018	-0.063	-0.004	-0.019
	Unsafe neighborhood	0.001	0.004	0.007	0.033
	Public school	-0.011	-0.040	-0.011	-0.053
	Reading ability at kindergarten	-0.022	-0.078	-0.007	-0.034
	Total	-0.034	-0.121	-0.024	-0.115
	N	4460		4460	

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE: * p<0.05; ** p<0.01; ***p<0.001.

Appendices

Table A3. Summary statistics of the case-complete sample

	Mean		Differences	p-values
	Obese	Normal-Weight		
Outcomes				
Reading	-0.155	0.141	-0.295	***
	(1.199)	(1.093)		
Math	-0.081	0.198	-0.279	***
	(1.063)	(0.936)		
Pathways				
Reduced parental educational expectation	0.330	0.188	0.142	***
	(0.471)	(0.391)		
Internalizing behavioral problems	1.724	1.554	0.170	***
	(0.567)	(0.504)		
School Absence	4.238	3.968	0.270	***
	(1.547)	(1.540)		
Approaches to learning	2.978	3.175	-0.196	***
	(0.661)	(0.649)		
Controls				
Girl	0.407	0.490	-0.083	***
	(0.492)	(0.500)		
Age	11.089	11.089	0.000	
	(0.365)	(0.349)		
Birth weight	7.732	7.414	0.318	***
	(1.279)	(1.258)		
Family Income (log)	10.548	10.860	-0.311	***
	(0.763)	(0.731)		
Mother's Years of Schooling	13.087	14.149	-1.062	***
	(2.591)	(2.530)		
Father's Occupation (% college graduates)	0.172	0.278	-0.106	***
	(0.215)	(0.287)		
Neighborhood Unsafe to Play	0.197	0.150	0.047	**
	(0.398)	(0.357)		
Public School	0.907	0.846	0.061	***
	(0.291)	(0.361)		

Reading IRT Scale Score at Kindergarten	28.803	31.245	-2.442	***
	(8.815)	(9.879)		
N	538	1,756		

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE: * p<0.05; ** p<0.01; ***p<0.001.

Table A4. Obesity and non-cognitive skills, net of family background for the case-complete sample

	Reduced Educational Expectation	Internalizing Behavioral Problems	School Absence	Approaches to Learning
Obesity	0.248**	0.147***	0.230***	-0.125***
	(0.124)	(0.029)	(0.079)	(0.033)
Girl	-0.243**	-0.079***	0.015	0.341***
	(0.115)	(0.022)	(0.065)	(0.026)
Age	0.542***	-0.021	0.194**	0.024
	(0.160)	(0.031)	(0.093)	(0.038)
Birth weight	0.040	-0.018**	0.029	0.032***
	(0.044)	(0.009)	(0.025)	(0.010)
Family Income (log)	-0.258***	-0.034**	-0.147***	0.057**
	(0.070)	(0.015)	(0.042)	(0.023)
Mother's Years of Schooling	-0.176***	-0.006	-0.029*	0.005
	(0.030)	(0.005)	(0.015)	(0.006)
Father's Occupation (% college graduates)	-1.405***	-0.032	0.091	0.093*
	(0.298)	(0.042)	(0.123)	(0.050)
Neighborhood Unsafe to Play	-0.111	0.071**	-0.087	-0.067*
	(0.157)	(0.034)	(0.093)	(0.038)
Public School	0.272*	0.017	-0.008	0.038
	(0.164)	(0.026)	(0.080)	(0.033)
Reading IRT Scale Score at Kindergarten	-0.066***	-0.004***	-0.007**	0.011***
	(0.010)	(0.001)	(0.003)	(0.001)
Constant	-0.478	2.532***	3.793***	1.428***
	(1.962)	(0.378)	(1.143)	(0.504)
N	2294	2294	2294	2294
Adjusted R^2		0.050	0.022	0.137

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE:
[a] I use linear regression to estimate the effect of obesity on work habit, internalizing behavioral problem and school absence, and logistic regression to estimate that on low parental educational expectation. The coefficients of obese represent percentage points (dy/dx) associated with moving from normal weight to obesity. * p<0.05; ** p<0.01; ***p<0.001.
[b] Control variables include gender, age, birth weight, family income (log), maternal education, paternal occupation, unsafe neighborhood and attending public school.

Table A5. Estimated relative importance of four mechanisms to explain the obesity penalty in reading scores from regression for the case-complete sample

	Models				
	1	2	3	4	5
Obesity	-0.096*	-0.073	-0.045	-0.043	-0.028
	(0.051)	(0.050)	(0.050)	(0.050)	(0.049)
Reduced parental educational expectation		-0.483***	-0.450***	-0.448***	-0.397***
		(0.067)	(0.065)	(0.066)	(0.064)
Internalizing behavioral problems	0.113***	0.092**	0.077**	0.079**	-0.016
	(0.041)	(0.040)	(0.039)	(0.040)	(0.040)
School Absence	-0.095	-0.063	-0.070	-0.071	-0.081
	(0.068)	(0.067)	(0.066)	(0.067)	(0.066)
Approaches to learning	0.046***	0.048***	0.045***	0.044***	0.036**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
Girl	0.118***	0.096***	0.091***	0.088***	0.079***
	(0.030)	(0.027)	(0.027)	(0.027)	(0.026)
Age	0.054***	0.041***	0.041***	0.041***	0.042***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Birth weight	0.242***	0.188***	0.185***	0.181***	0.161**
	(0.070)	(0.068)	(0.068)	(0.068)	(0.067)
Family Income (log)	-0.124**	-0.128**	-0.113*	-0.112*	-0.100*
	(0.063)	(0.062)	(0.062)	(0.062)	(0.060)
Mother's Years of Schooling	-0.131***	-0.113***	-0.111***	-0.112***	-0.128***
	(0.042)	(0.042)	(0.041)	(0.042)	(0.041)
Father's Occupation (% college graduates)	0.032***	0.029***	0.028***	0.028***	0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Neighborhood Unsafe to Play			-0.200***	-0.201***	-0.057
			(0.043)	(0.044)	(0.045)
Public School				-0.002	0.005
				(0.012)	(0.012)
Reading IRT Scale Score at Kindergarten					0.317***
					(0.035)
Constant	-2.155**	-1.913**	-1.423*	-1.377*	-2.233***
	(0.848)	(0.827)	(0.829)	(0.832)	(0.825)

N	2294	2294	2294	2294	2294
Adjusted R^2	0.214	0.244	0.253	0.252	0.281

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE:
[a] I use linear regression to estimate the effect of obesity and four mechanisms on reading scores. * p<0.05; ** p<0.01; ***p<0.001.
[b] Control variables include gender, age, birth weight, cans of soda consumed, days of intensive exercise, hours of TV viewing , family income (log), maternal education, paternal occupation, unsafe neighborhood and attending public school.

Table A6. Estimated relative importance of four mechanisms to explain the obesity penalty in math scores from regression for the case-complete sample

	Models				
	1	2	3	4	5
Obesity	-0.099**	-0.084*	-0.054	-0.043	-0.028
	(0.045)	(0.045)	(0.044)	(0.044)	(0.043)
Reduced parental educational expectation	-0.177***	-0.191***	-0.206***	-0.203***	-0.302***
	(0.035)	(0.035)	(0.035)	(0.034)	(0.034)
Internalizing behavioral problems	-0.037	-0.016	-0.022	-0.015	-0.026
	(0.062)	(0.061)	(0.061)	(0.061)	(0.060)
School Absence	0.056***	0.058***	0.054***	0.055***	0.046***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Approaches to learning	0.121***	0.107***	0.101***	0.093***	0.083***
	(0.030)	(0.029)	(0.028)	(0.028)	(0.027)
Girl	0.053***	0.044***	0.044***	0.042***	0.043***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.199***	0.162***	0.159***	0.162***	0.142**
	(0.061)	(0.060)	(0.059)	(0.059)	(0.057)
Birth weight	-0.092*	-0.095*	-0.079	-0.083	-0.071
	(0.055)	(0.055)	(0.054)	(0.054)	(0.052)
Family Income (log)	-0.014	-0.002	0.000	-0.002	-0.018
	(0.036)	(0.036)	(0.036)	(0.036)	(0.035)
Mother's Years of Schooling	0.032***	0.030***	0.029***	0.029***	0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Father's Occupation (% college graduates)		-0.324***	-0.288***	-0.283***	-0.230***
		(0.050)	(0.050)	(0.050)	(0.049)
Neighborhood Unsafe to Play			-0.214***	-0.201***	-0.051
			(0.036)	(0.037)	(0.038)
Public School				-0.049***	-0.041***
				(0.011)	(0.011)
Reading IRT Scale Score at Kindergarten					0.330***
					(0.028)
Constant	-2.787***	-2.624***	-2.101***	-1.912**	-2.803***

	(0.769)	(0.754)	(0.749)	(0.752)	(0.740)
N	2294	2294	2294	2294	2294
Adjusted R^2	0.246	0.263	0.277	0.282	0.321

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006): NOTE:
[a] I use linear regression to estimate the effect of obesity and four mechanisms on reading scores. * p<0.05; ** p<0.01; ***p<0.001.
[b] Control variables include gender, age, birth weight, cans of soda consumed, days of intensive exercise, hours of TV viewing , family income (log), maternal education, paternal occupation, unsafe neighborhood and attending public school.

Table A7. Estimated contributions of four mechanisms to the observed differences in test scores between obese and normal-weight students from the case-complete sample.

		Reading		Math	
		Test scores (SD)	Proportion total differences	Test scores (SD)	Proportion total differences
Differential					
	Normal-weight	0.357		0.345	
	Obesity	0.152		0.191	
	Difference	0.205		0.154	
Endowments					
	Low educational expectation	0.031	0.150	0.009	0.057
	Internalizing behavior problems	0.001	0.005	0.014	0.094
	School absence	-0.007	-0.032	0.007	0.046
	Work habits	0.075	0.364	0.068	0.444
	Girl	-0.009	-0.043	-0.027	-0.174
	Age	0.004	0.020	0.002	0.014
	Birth weight	0.021	0.101	0.006	0.038
	Family income (log)	-0.008	-0.041	-0.006	-0.038
	Maternal education	0.002	0.011	0.048	0.315
	Paternal occupation	0.045	0.220	0.039	0.252
	Unsafe neighborhood	0.005	0.025	-0.002	-0.013
	Public school	0.019	0.094	0.015	0.099
	Reading ability at kindergarten	0.040	0.193	0.035	0.228
	Total	0.219	1.067	0.210	1.360
Coefficients					
	Low educational expectation	0.029	0.140	-0.041	-0.269
	Internalizing behavior problems	-0.132	-0.643	0.020	0.128
	School absence	-0.126	-0.614	-0.085	-0.549
	Work habits	-0.396	-1.930	-0.205	-1.332
	Girl	0.028	0.135	-0.021	-0.137

	Age	2.025	9.876	0.865	5.615
	Birth weight	0.873	4.259	0.508	3.298
	Family income (log)	0.916	4.470	1.040	6.755
	Maternal education	0.572	2.789	-0.189	-1.226
	Paternal occupation	-0.061	-0.296	-0.058	-0.375
	Unsafe neighborhood	0.022	0.105	-0.025	-0.163
	Public school	0.123	0.602	0.168	1.089
	Reading ability at kindergarten	-0.029	-0.141	0.121	0.784
	Constant	-3.836	-18.715	-2.115	-13.736
	Total	0.008	0.037	-0.018	-0.118
Interaction					
	Low educational expectation	-0.012	-0.056	0.017	0.108
	Internalizing behavior problems	0.015	0.072	-0.002	-0.014
	School absence	0.009	0.044	0.006	0.039
	Work habits	-0.025	-0.123	-0.013	-0.085
	Girl	0.008	0.039	-0.006	-0.040
	Age	-0.004	-0.019	-0.002	-0.011
	Birth weight	-0.033	-0.160	-0.019	-0.124
	Family income (log)	0.025	0.123	0.029	0.187
	Maternal education	0.044	0.212	-0.014	-0.093
	Paternal occupation	-0.029	-0.142	-0.028	-0.180
	Unsafe neighborhood	-0.005	-0.023	0.005	0.036
	Public school	-0.013	-0.064	-0.018	-0.116
	Reading ability at kindergarten	-0.002	-0.009	0.008	0.050
	Total	-0.022	-0.106	-0.037	-0.243
	N	2,294		2,294	

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE: *p<0.05; **p<0.01;***p<0.001

Table A8. Weight-specific effects of pathways on test scores for the case-complete sample

	Reading		Math	
VARIABLES	Obese	Normal-weight	Obese	Normal-weight
Reduced educational expectations	-0.482***	-0.349***	-0.157*	-0.252***
	(0.111)	(0.077)	(0.092)	(0.058)
Internalizing behavioral problems	-0.014	-0.072	-0.096	-0.034
	(0.074)	(0.055)	(0.084)	(0.043)
School absence	0.028	-0.000	-0.014	-0.048***
	(0.025)	(0.014)	(0.030)	(0.012)
Approaches to learning	0.416***	0.291***	0.363***	0.322***
	(0.065)	(0.041)	(0.063)	(0.032)
Girl	-0.139*	0.026	-0.262***	-0.308***
	(0.083)	(0.045)	(0.078)	(0.038)
Age	-0.118	-0.075	0.116	-0.081
	(0.129)	(0.077)	(0.120)	(0.068)
Birth weight	-0.049	0.063***	0.000	0.061***
	(0.035)	(0.017)	(0.029)	(0.014)
Family Income (log)	0.084	0.072***	0.084	0.084***
	(0.070)	(0.026)	(0.070)	(0.027)
Mother's Years of Schooling	0.039	0.044***	0.054**	0.039***
	(0.026)	(0.010)	(0.025)	(0.008)
Father's Occupation (% college graduates)	0.227	0.148**	0.289**	0.122**
	(0.167)	(0.073)	(0.141)	(0.062)
Neighborhood Unsafe to Play	-0.078	-0.109	0.077	-0.127**
	(0.105)	(0.073)	(0.100)	(0.062)
Public School	-0.212**	-0.108**	-0.119	0.008
	(0.107)	(0.044)	(0.086)	(0.038)
Reading IRT Scale Score at Kindergarten	0.031***	0.025***	0.031***	0.026***
	(0.006)	(0.002)	(0.006)	(0.002)
Constant	-1.725	-2.347**	-4.483***	-2.212***
	(1.772)	(0.937)	(1.606)	(0.829)
N	524	1770	524	1770
Adjusted R^2	0.277	0.275	0.281	0.331

SOURCE: The Early Childhood Longitudinal Study-Kindergarten Cohort (1998-2006)
NOTE: *p<0.05; **p<0.01;***p<0.001

Chapter III Disparate Disadvantage: The Heterogeneous Effects of Childhood Obesity on Academic Achievement

Abstract

Past studies have shown that, on average, obese students fall behind their non-obese peers in school performance. However, the negative effects of obesity may not be equal for all students and the underlying pathways may vary among individuals. To identify specific groups at greater risk, I use a quantile regression approach to investigate the differential effects of obesity across the distribution of reading and math test scores. I find that students with low and mid-level test scores are disproportionately affected by excess weight. Poor work habits are the major factor underlying poor test scores among low-achieving students, while low educational expectations are the main underlying mechanism among median-level students. These findings suggest that to effectively alleviate the deleterious effects of childhood obesity on school performance, policy interventions should include specific measures to help low-achieving students.

Keywords: quantile regression, obesity, academic achievement

Introduction

A growing number of studies have found substantial obesity penalties in academic achievement among elementary and middle school students (Averett and Stifel 2010; Crosnoe 2007; Datar, Sturm and Magnabosco 2004; Han 2010a; Sabia 2007). Poor work habits, reduced educational expectations, and behavioral problems are important pathways that account for the lower test scores of obese students (Crosnoe 2007; Han 2010b; Sigfusdottir, Kristjansson and Allegrante 2007). However, weight status may not affect all obese students equally. Some scholars posit that low-achieving obese students are at greater risk of falling behind because they lack the good work habits necessary to achieve academic prominence. Others hypothesize that high-achievers endure the largest obesity penalty because, more often being in families with high socioeconomic status, they endure a stronger weight stigma. Given the widespread nature of childhood obesity and the current budget constraints in U.S. schools, decisions about the allocation of resources depend heavily on the proper identification of specific target groups. However, most previous studies focus on the aggregate obesity effect for all students, and are therefore insufficient to provide guidance for policy design. To fill this gap, in the current study I evaluate the heterogeneous effects of obesity on reading and math test scores and address the following questions: Which students are most vulnerable to the disadvantageous effects of obesity? Do the mechanisms by which weight influences academic achievement differ by group?

To investigate this issue, I use longitudinal data on student achievement, and a quantile regression approach. The analysis differs from earlier studies of the effects of obesity in several respects. First, I implement a quantile regression approach with longitudinal data to better discern the heterogeneous effects. Unlike earlier studies, which used summary measures of reading achievement, the current study differentiates the obesity penalty across the entire distribution of reading and math test scores to identify which students are at greater risk. Second, this study explores potential variation in the causal pathway that produces the obesity penalty. The identification of heterogeneous mechanisms will help inform policy interventions that can curb the deleterious effects of obesity penalties. Third, this study focuses on 4,000 students in middle school (eighth grade), while earlier studies lumped children and adolescents together. Because very few students drop out of school this early, the investigation does not suffer from the potential selection bias that differential drop-out rates introduce in comparisons of achievement later in high school (Lee, Winfield and Wilson 1991).

I find that obesity disproportionately affects students with low and mid-level test scores. Poor work habits are the major factor underlying poor test scores among low-achieving students, while low educational expectations are the main underlying mechanism among median-level students. These findings suggest that to effectively alleviate the deleterious effects of childhood obesity on school performance, policy interventions should include specific measures to help low-achieving students.

Variations in the mechanisms producing the obesity penalty

Behavioral problems, poor work habits, reduced educational expectations and school absence are four major explanations of poor academic achievement among obese students. However, both the magnitude of the obesity impact and the underlying mechanism through which it operates may differ across the spectrum of previous academic achievement.

The need perspective

Proponents of the need perspective argue that low-achieving students may endure the largest obesity penalties in test scores. Low-achieving students, in general, have a heightened need for the resources important to skill development, and are sensitive to parental expectations and the quality of parental investment (Pomerantz, Wang and Ng 2005). Once equipped with these resources, they are more likely to compensate with positive work habits, and these improved habits help students acquire and build on basic academic skills. Thus, low-achieving students may reap greater benefits from good work habits and parental investment than high-achieving children (Bodovski and Farkas 2007; Lee and Bowen 2006; Li-Grining et al. 2010). In contrast, high-achieving students may already possess adaptive work habits and other resources necessary to achieve academic success (Newman et al., 1998).

Scholars arguing from this perspective have proposed that obesity penalties are larger for low-achieving students because the effects of 1) weight stigma and 2) school absence on test scores are larger for low-achieving students than for high-achieving students. First, low-achieving students may respond to weight stigma with negative attitudes, while high-achieving students respond more positively. Past studies have shown that obese students are more likely to develop behavioral problems that disproportionately affect low-achieving students (Rimm and Rimm 2004). Low-achieving students often see academic success as unattainable and consider themselves incompetent and worthless. To protect their self-worth, they often show disregard for the values and standards of schooling by disengaging, which may be manifested by sleeping in class, not completing assignments, or skipping school (Kelly and Turner 2009). In contrast, high-achieving students may adopt a more positive attitude toward weight stigma. Academic success can boost their confidence and shield them from the harmful effects of many negative labels. These students may also develop helpful ways to deal with weight stigma and cope with behavioral problems. Second, low-achieving students require more time to master class material (Zohar and Peled 2008). They are more likely to fall behind in school when they miss class. The work of Ready (2010) showed that the negative effects of absenteeism were stronger for children with a lower socioeconomic status (SES). Thus, even if the degree of weight stigma is similar for low- and high-achieving students, the stronger impact of the stigma among low-achieving students suggests greater obesity penalties.

The socioeconomic variation perspective

In contrast, advocates of the socioeconomic variation perspective argue that high-achieving students may face the greatest risks of obesity in school performance because the degree of weight stigma is much higher among those with high socioeconomic status. According to this perspective, the extent to which obesity elicits negative treatment from others is contingent upon social context. Upper-middle class Americans are less likely to be obese, more likely to hold anti-obesity attitudes, more likely to view thinness as a physical ideal, and more likely to view obesity as a consequence of laziness (Warschburger 2005). Research has found stronger negative anti-fat attitudes among children attending schools with high social status (Wardle, Volz and Golding 1995). Therefore, high-achieving obese students, who disproportionately belong to a social stratum in which obesity is less statistically and culturally normative, may be more likely than low-achieving obese students to experience and perceive interpersonal mistreatment.

Indeed, studies of adults have found a similar pattern in the workplace; empirical findings suggest that obese professional workers report significantly more perceived interpersonal mistreatment than obese persons of lower socioeconomic status in the United States (Warschburger 2005), and the obesity differences in income are larger for white-collar working women in the upper class than those for manual workers (Sarlio-Lahteenkorva, Silventoinen and Lahelma 2004). These findings suggest that high-achieving students, who disproportionately have high SES, may endure the largest obesity penalty in test scores.

Previous empirical research

Most previous studies have produced average estimates of the obesity gap in academic achievement for all students (Averett and Stifel 2010; Datar, Sturm and Magnabosco 2004; Rimm and Rimm 2004); only one study has addressed the differential effects of obesity by test scores (Eide, Showalter and Goldhaber 2010). Using a quantile regression approach, Eide and colleagues (2010) found that being overweight (BMI >90th percentile) was correlated with *higher* reading scores among low-achieving students, but *lower* reading scores among high-achieving students for children in the second-wave of the Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID).

However, the study had three potentially problematic limitations. First, the obesity premium reported in the study is inconsistent with obesity penalties found in prior studies. Because they employed a cross-sectional design and omitted measures of physical activity, Eide and colleagues (2010) have speculated that the obesity premium may result from more study times and lower levels of physical activity among overweight children. Yet, two studies have shown consistent obesity gaps in test scores after controlling for actual physical activity levels (Han 2010a; Sigfusdottir, Kristjansson and Allegrante 2007). In addition, a qualitative study found that obese children spend about the same amount of time doing homework, but still fall behind, largely due to poor work habits and poor self-confidence (Rimm and Rimm 2004). Second, the authors did not investigate whether the underlying pathways are the same for all students. Third, using a broad sample of children and adolescents (ages 5 through 18) likely introduced additional selection bias due to some students dropping out of school. Because some adolescents dropped out of school before age 18, the study sample may include only students who have maintained satisfactory academic progress, and thus overestimate the impact of obesity. Additionally, the broad age group makes it difficult to identify the particular age groups that are most affected.

I use longitudinal data and a quantile regression technique to model the varying effects of obesity on test scores. A major drawback of ordinary least squares regression (OLS) is that it is highly sensitive to outliers, and mean estimates may mask important differences between groups. Quantile regression, in contrast, estimates the median values, which are not prone to outliers, and yields specific point estimates of obesity across the distribution of test scores to reveal which groups are at greater risk. To reduce the potential selection bias associated with early drop-outs, I restrict the analytic sample to a cohort of young adolescents that are relatively homogeneous in terms of grade level. Controlling for important covariates, including physical activity level, TV viewing, and nutritional intake, in the quantile regression models minimizes omitted variable bias. I extend the analysis by assessing the potential pathways that may explain the obesity gaps in academic achievement. A more thorough understanding of group-specific pathways can provide solid evidence for effective policy interventions.

I am cautious about interpreting the differential obesity penalties on reading and test scores as causal effects. Although I control for several factors, there may be unobserved variables that simultaneously determine both obesity and reading scores. For example, school budget deficits may limit students' access to physical activity, and also restrict their access to high-quality teachers. If this is the case, poor achievement among obese students cannot be attributed solely to obesity itself.

Research hypotheses

This study examines 1) the differential relationships between obesity and reading ability among eighth graders across the distribution of reading and math test scores, and 2) potential variations in the underlying causal pathways. I hypothesize that the effect of obesity is greatest among low-achieving students, and that this pattern occurs because certain characteristics associated with obesity—poorer work habits, lower parental educational expectations, less behavioral stability, and less consistent school attendance—exert the largest impact on low-achieving students, .

Methodology

Data and sample

To test these hypotheses, I use the Early Childhood Longitudinal Study-Kindergarten cohort dataset (ECLS-K), which consists of nationally representative data collected by the Department of Education. Beginning in the fall of 1998, when they entered kindergarten, the survey followed 21,000 children through the spring of 2006.[25] By eighth grade, 8,960 children remained in the study.

The ECLS-K has several advantages for the current study. First, it has a relatively comprehensive measure of determinants of obesity and achievement, including demographic characteristics, birth condition, family background, nutrition, physical activity, school and neighborhood features. This set of covariates enables us to reduce biases from omitted variables. In particular, it includes indicators of work habits, physical activity, nutrition intake, and neighborhood characteristics which are not available in past studies. Second, it has relatively refined measures of behavioral problems, educational expectations, school absence and work habits. Its measures of internalizing behavioral problems from teacher's evaluation have higher degree of reliability than reports from parents or students themselves. Also, the record of school absence, derived from school administration data, is more reliable than student self reports used by other author (Daniels 2008).

[25] The ECLS-K refreshed its sample by adding 167 children in the fall of first grade (Wave III), and only collected data from 30% of the original sample during this wave.

I restricted the sample to 4,460 white children with complete data on Item Response Theory (IRT)-scale test scores and obesity status at fifth and eighth grade.[26] The case-complete sample has 2,631 white children. Nearly 39 percent of these children are classified as obese, with a BMI above the 95th percentile in both fifth and eighth grade. I use the sample of 2,631 children with complete data on all covariates in the primary analysis, and supplement the primary results with an analysis using the imputed sample of 4,460 children.

Dependent variables

The outcomes in this study include eighth-grade IRT-scale test scores in reading and math. The reading test measures students' skills in nine dimensions: letter recognition, beginning sounds, ending sounds, sight words, comprehension of words in context, literal inference, extrapolation, evaluation, and critical evaluation of literal works. The math test evaluates students' skills in number and shape, relative size, ordinarily and sequence, addition and subtraction, division and multiplication, place value, rate and measurement, fractions, area, and volume. The reading IRT scale scores have a mean of 171 points and a standard deviation of 27.6 points, and the math IRT scale scores have a mean of 142 points and a standard deviation of 22 points. Both scores are slightly skewed toward the bottom. To facilitate the

[26] I limit the analytic sample to white children because there are not enough African American and Hispanic children to allow effective matching.

comparison across subjects, I use the standardized scores in standard deviation as unit of analysis.

Independent variables

The independent variable is a student's obesity status (>95th percentile of the BMI z-score) both at fifth and eighth grade. The reference group is the 5th-75th percentile of the BMI z-score distribution. As a sensitivity test, I also use the extreme obesity (BMI>97th percentile) as the independent variable.

Mediating variables

School absence, work habits, behavioral problems, and reduced parental educational expectations are included as mediating variables. School absence is obtained from school administrative data and measures the total days absent in fifth grade (i.e., the 2003-2004 school year), ranging from 1 to 12. Work habits is measured via teacher ratings that range from 1 to 4, and is an overall measure of attentiveness, task persistence, eagerness to learn, learning independence, flexibility, and organization in the classroom. The measure of internalizing behavioral problems comes from teacher ratings of anxiety, loneliness, low self-esteem, and sadness; values range from 1 to 4. Reduced parental educational expectations is indicated by a dummy variable that equals 1 if a parent does not expect his or her child to attain a four-year college degree.

Control variables

To mitigate omitted variable bias, I control a number of variables that past studies have found to influence both obesity status and test scores. Birth weight is a contiguous variable based on parental report in kindergarten. Levels of physical activity and nutrition are indexed by the frequency of TV viewing, 20-minute periods of intensive exercise, and soda consumption in a typical week. Maternal education is measured by years of schooling, and family income is the total income of all persons in a child's household, including salaries as well as other earnings, interest payments, retirement benefits, and other income. A neighborhood characteristic is measured by parental assessment of safety to play outside. School type is measured by public school attendance in third grade. School-entry readiness is measured by students' reading test scores in kindergarten.

Methods

I use quantile regression to reveal potential differential relationships between obesity and test scores. Quantile regression estimates the effect of explanatory variables on the dependent variable at different points of the dependent variable's conditional distribution (that is, conditional on the other explanatory variables) (Koenker and Hallock 2001). Quantile regression yields specific point estimates of obesity across the distribution of reading and math test scores. After estimating the simultaneous model, I used an F-test on each possible pair of estimated quantiles to test whether obesity's effects differed significantly by quantile.

The specification of a quantile regression is as follows (Budig and Hodges 2010): Let (y_i, x_i), i = 1,…,n, be a sample from some population where x_i is a K × 1 vector of regressors,

$$\begin{gathered} y_i = x_i'\beta_\theta + u_\theta \\ Quant_\theta(y_i|x_i) = x_i'\beta_\theta \\ Quant_\theta(u_{\theta i}|x_i) = 0 \end{gathered} \qquad (1)$$

and where Quantθ(y_i|x_i) denotes the conditional quantile of y_i, conditional on the regressor vector | x_i. The linear model for the θth quantile solves the following minimization to obtain β:

$$min \frac{1}{n}\left\{\sum_{i:y_i \geq x_i'\beta_\theta} \theta|y_i - x_i'\beta_\theta| + \sum_{i:y_i \leq x_i'\beta_\theta}(1-\theta)|y_i - x_i'\beta_\theta|\right\} \qquad (2)$$

The dependent variable, Y, is reading or math test score.

I estimate the quantile regressions at the nine points of the test score distribution from 0.10 quantile (or 10th percentile) to the 0.90 quantile (or 90th percentile). Wald test is used to test whether any particular point estimate are statistically the same. If obesity affects all students equally, the coefficient estimates for all the nine points would be similar, and OLS models would provide a reasonable summary of the data. However, the effect of obesity may differ across quantiles. If the (positive) 0.10 quantile estimates are larger than the 0.90 estimates, the dispersion in the data has decreased; which means the students at the bottom of the distribution are disproportionately affected by the independent variable. Conversely, if the (positive) 0.90 coefficients are larger than the 0.10 quantile, the distribution has expanded, indicating that the students at the top of the distribution are disproportionately affected.

Missing values

An examination of the patterns of missing data in the covariates reveals that 12 of 20 covariates have missing values for at least some respondents, and the missing values for 4 variables (reading scores in kindergarten, math scores in kindergarten, father's occupational status, and free lunch recipient) account for the majority of missing data points (around 75 percent). Assuming missing data occurred randomly, I fill in the missing values using imputation by chained equations implemented via the ICE procedure in STATA (Raghunathan et al. 2001; Van Buuren and Oudshoorn 2000). Imputation yields five imputed samples of 4,460 cases. Compared to children in the complete sample, those with missing values have lower math scores in kindergarten and are more likely to receive free lunch and live in unsafe neighborhoods. Given these differences, I expect the analysis of the imputed sample will yield more conservative results.

Results

Characteristics of obese and normal-weight students across reading distributions

Table 11 presents the unadjusted means and standard deviations of selected variables at the <0.2, 0.5-0.6, and >0.9 quantiles of the reading score distribution by obesity status. Group differences are measured by a t-test for paired means.

In terms of reading ability measures, the results in the first section clearly show that obese students have lower test scores than their thinner counterparts across the distribution. The observed obesity differences in test scores are generally larger among students at the bottom of the reading score distribution and smaller among students at the top.

Obese students at the bottom of the reading score distribution generally have much lower levels of non-cognitive skills than their thinner peers. Compared to their thinner counterparts, among these low-achieving students, low parental expectations are more common, internalizing behavioral problems are more severe, the duration of school absences are longer, and work habits are poorer. Among median and high-achieving students, however, the differences in parental expectations and school absence by obesity status are smaller and insignificant. For example, among low-achieving students, 44.6 percent of parents of obese children have low expectations, which is roughly 10 percentage points lower than for normal-weight students. Among high-achieving students, low parental expectations are rare, regardless of weight status.

In terms of background variables, obese students across reading quantiles are more likely than their normal-weight counterparts to come from disadvantaged families. The mothers of obese respondents have 0.3-1.3 fewer years of schooling, and respondents' families have lower incomes. Public school attendance and entering school with low reading scores are more common among obese students than non-obese students at the bottom of the reading score distribution, but differences in these two variables by weight status appear even larger among students at the top. In every quantile, obese students, in average, have higher birth weight and watch more hours of TV every week; however, in terms of gender, age, weekly soda consumption, and intensive exercise, obese students do not differ significantly from their normal-weight counterparts in any of the reading quantiles.

Who is at the greatest risk of enduring obesity penalty in reading?

The key focus of this study is the potential variance in the obesity penalty across the reading achievement distribution. The need perspective suggests that low-achieving students are at greater risk of obesity penalty because of larger impacts of the pathways on test scores, while the socioeconomic variation perspective predicts larger obesity penalty among high-achieving students because of stronger weight stigma. To test these hypotheses, I conduct a simultaneous quantile regression of the effects of obesity on reading; estimates are presented in Table 12.

As shown in Row1 of Table 12, among high-achieving students, excess weight has no significant effect on reading, while among low-achieving students and median students, obesity does affect reading. The degree of the obesity penalties for reading scores is largest among students at the bottom of the reading score distribution. Obese children score about 0.422 SDs lower at the 0.1 quantile, and 0.08 SDs lower at the 0.5 quantile, compared with their thinner counterparts. Results of the Wald test suggest significant differences between the obesity gaps at the two lower quantiles and the gap at the 0.9 quantile. An analysis of the imputed sample yields similar findings, and the effect sizes for most quantile points (except the 0.1 and 0.8 quantiles) are close to those in the case-complete sample (results in Table A9). Overall, these findings support the need perspective and suggest that obesity has a pronounced effect on the reading ability of the most vulnerable students, decreasing test scores to a greater extent for these students than for the students at the top of the distribution.

What factors have explained the variation in obesity penalty in reading?

What factors are responsible for the particularly large impacts of obesity among low-achieving white students? Table 12 shows the differential effects of obesity on reading scores for simultaneous quantile regressions.

I argue that low parental educational expectations, behavioral problems and poor work habits are three channels through which weight stigma leads to underachievement. Model 2 adds parental educational expectations and Model 3 adds internalizing behavioral problems. These two measures explain a significant portion of the obesity penalties for median students, but do not completely account for the penalties among low-achieving students. For example, the estimated obesity penalty for median students falls to insignificance after controlling parental educational expectations and behavioral problems (Column 5). In addition, the magnitudes of the obesity penalties are decreased by half. In contrast, among students at the bottom of the distribution, the estimated obesity gaps fall slightly, but remain significant. These findings suggest that forces other than weight stigma may influence obesity penalties among low-achieving students.

Model 4 adds work habits to the analysis. The results clearly indicate that work habits explain the largest proportion of the obesity penalty among low-achieving students. Among low achievers in the 0.2 quantile, the estimated obesity penalty decreased from 0.148 to 0.082 SDs and is no longer statistically significant. Similar results occurred for those in the 0.1 and 0.3 quantile distributions. In results not shown, among the lowest achievers, controlling for poor work habits alone attenuates the estimated obesity penalty from 0.42 to 0.22 SDs. In contrast, adding the measure of work habits does not further reduce the obesity penalties for median and high-achieving students. These findings confirm the hypothesis that poor work habits is an important mediating factor for low-achieving students. In addition, results from

Model 5 suggest that school absence is not an important mechanism for explaining the obesity penalty; almost all of the obesity coefficients remain the same after controlling for school absence.

To visually present the joint impacts of weight stigma and work habits, Figure 4 compares the obesity penalties in overall reading scores from the baseline model (Model 1) and Model 4, which simultaneously controls for parental educational expectations, behavioral problems, and work habits. These three mediating factors collectively explain the largest proportion of obesity penalties for students at the 0.1, 0.2, and 0.6 quantiles of the distribution, but have very little influence on obesity penalties among high-achieving students.

In summary, these findings support the hypothesis that students with the lowest reading performance incur the largest obesity penalties. The obesity penalty for these students is a function of poor work habits, low parental expectations, and behavioral problems. Among median students, differences in parental educational expectations and behavioral problems account for the majority of the obesity penalty.

Who is at the greatest risk of enduring obesity penalty in math?

To assess the varying effects of obesity on math scores, I perform the simultaneous quantile regression on math test scores and report the results in Table 13.

The analysis described above shows that the reading scores of high-achieving students are not affected by obesity. Are these students also immune to the obesity penalties in math? Results in Row 1 of Table 13 show just the opposite. First, in contrast to the trivial effects on reading, obese students in the 0.8 and 0.9 quantiles score 0.086 standard deviations and 0.078 standard deviations, respectively, lower than their thinner counterparts. The effect size is almost one-third of the obesity penalty experienced by students at the 0.1 quantile of the math score distribution. Second, as opposed to the substantial obesity penalties for low-achieving and median students in reading scores, excess weight does not significantly affect the math scores of these students. Third, the obesity effects are also smaller in math than reading for students in the 0.1 quantile and median students in the 0.6 and 0.7 quantiles. These findings indicate that, with regard to math scores, high-achieving students and very low-achieving students are disproportionately affected by obesity.

What factors have explained the variation in obesity penalty in math?

What accounts for the obesity gap in math among high-achieving students? The socioeconomic variation perspective suggests that high-achieving students, who disproportionately come from families with high socioeconomic status, often face stronger weight stigma. To test these hypotheses, I perform quantile regression analyses similar to the ones conducted for reading, and report the results in Table 13.

First, the results for the 0.7 and 0.9 quantiles generally support the socioeconomic variation perspective. Nearly three-quarters of the obesity gap in math for the 0.9 quanitle can be explained by reduced parental educational expectations and behavioral problems. Adding the measure of parental educational expectations alone reduces the negative impact of obesity for students in the 0.7 quantile to insignificance. These findings suggest that although high-achieving students may possess the resources and work habits necessary for cognitive development, they may still pay a price for excessive weight because of persistent weight stigma.

Second, the results for the 0.1 and 0.6 quantile students highlight the importance of behavioral problems in mediating the negative impact of obesity on math. Unlike the predominant role of work habits in explaining poor reading performance, behavioral problems almost completely account for the obesity gaps in math for students at the bottom of the math distribution. This same pattern holds for students in the 0.6 quantile. Notably, however work habits remain an important mediating factor for students in the 0.8 quantile—the obesity penalty decreases about 80 percent when work habits are added.

Figure 5 compares the differential obesity penalties in the overall math score from the baseline model (Model 1) and Model 4, which simultaneously controls for parental educational expectations, behavioral problems, and work habits. Clearly, as with reading, these three mediating factors account for the estimated obesity penalties in math for both low-achieving and high-achieving students. Results from the imputed sample further confirm the finding that obesity is negatively associated with math scores for high-achieving students and very low-achieving students, and that parental educational expectations play a significant role in explaining the poor achievement of obese students (Table A10).

Discussion and conclusion

The objectives of this study are to identify the specific groups at the greatest risk of enduring obesity penalties in reading and math test scores, and to evaluate the mechanisms that explain these obesity penalties. The study provides a strong test of these questions by applying quantile regression to longitudinal data and controlling important covariates that were not available in past studies. The analysis extends current studies on similar topics by assessing the varying mechanisms for students at different levels of academic performance.

Regression results show that for reading, students at the bottom and middle of the achievement distribution incur substantial obesity penalties, while for math students at the top of the distribution score significantly worse than their thinner counterparts. In particular, the obesity gaps in reading are largest among students in the 0.1 quantile distribution; the gaps for this group are about 20 times larger than those for students at the 0.9 quantile. Further, these varying effects of obesity are attributed to different mediating factors. Among low-achieving students, poor work habits account for the majority of the score gaps in reading. For median students, persistent weight stigma, measured by reduced parental educational expectations and behavioral problems, is the most important factor explaining reading test score gaps associated with obesity. Similarly, among high-achieving students, weight stigma accounts for the majority of the math score gap.

The finding that the largest obesity penalties occur among low-achieving students supports the need perspective. A shortage of good work habits leads to poor test scores among those low-achieving students. These findings of work habits underscore the importance of improving academic engagement in promoting academic achievement among low-achieving students. Past studies have shown that small-group instruction that can be tailored to students' needs may be an effective strategy to increase engagement in elementary and middle school (Kelly and Turner 2009). However, the emphasis on work habits does not discredit the role of parental involvement. Indeed, some studies have found that higher parental expectations are particularly beneficial in boosting the grade point averages and teacher-rated academic competence of low-achieving ninth graders (Chen and Gregory 2009).

Consistent with the prediction of the socioeconomic variation perspective, high-achieving obese students score more poorly in math than their normal-weight counterparts. The obesity penalties are non-trivial, about one-third of those endured by low-achieving students. This finding highlights the pervasive effect of weight stigma among students with a higher socioeconomic status.

The finding that obesity penalties vary by academic achievement level differs from the *positive* impact reported by Eide, Showalter, and Goldhaber (2010). Three factors may explain this discrepancy. First, I control for measures of physical activity and TV viewing that was omitted in their study. Second, in contrast to cross-sectional data in their study, I employ quantile regression and longitudinal data to establish temporal order. Notably, because this was a non-experimental study, the results cannot support firm conclusions about the causal role of obesity in producing reading difficulties.

The differential effects of obesity on reading ability suggest topics for future research. This study focuses on white children due to the limited sample size of African American and Hispanic children. Given the differential degree of weight stigma across racial and ethnic groups, further analysis of racial differentials would shed light on the underlying pathways generating obesity penalties. Similarly, gender-specific analysis would advance the scholarly understanding of the specific mechanisms and related remedies to improve the academic performance of obese students.

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Table 11.Characteristics of obese and normal-weight students across the reading distribution

Quantile	≤0.2		0.5-0.6		≥0.9	
	Obese	Normal	Obese	Normal	Obese	Normal
Dependent Variables						
Reading scores (SD)	-0.873*	-0.654	-0.004*	0.181	0.480*	0.727
	(1.008)	(1.027)	(0.904)	(0.812)	(0.687)	(0.587)
Math scores (SD)	-0.627	-0.603	0.362	0.388	0.789*	0.890
	(0.077)	(0.049)	(0.053)	(0.026)	(0.053)	(0.018)
Mechanisms						
Low Expectations	0.446*	0.344	0.214	0.181	0.123	0.086
	(0.498)	(0.476)	(0.411)	(0.386)	(0.330)	(0.281)
Internalizing Behavioral Problems	1.834*	1.726	1.718*	1.576	1.58*	1.46
	(0.593)	(0.572)	(0.623)	(0.484)	(0.528)	(0.433)
School Absence	4.456*	4.104	4.04	3.941	3.945	3.754
	(1.447)	(1.516)	(1.657)	(1.575)	(1.647)	(1.532)
Approaches to Learning	2.669*	2.808	3.089	3.17	3.323*	3.46
	(0.599)	(0.653)	(0.640)	(0.629)	(0.590)	(0.544)
Control Variables						
Girls	0.349	0.402	0.432	0.507	0.478*	0.614
	(0.477)	(0.491)	(0.497)	(0.500)	(0.501)	(0.487)
Age	11.048	11.072	11.064	11.077	11.093	11.072
	(0.357)	(0.362)	(0.376)	(0.351)	(0.380)	(0.361)
Birth Weight (lbs)	7.533*	7.219	7.845*	7.406	7.526	7.421
	(1.396)	(1.320)	(1.487)	(1.258)	(1.437)	(1.283)
Weekly TV Hours	7.688	7.321	7.688*	6.295	7.762*	6.095
	(4.323)	(4.080)	(4.000)	(3.184)	(3.847)	(3.331)
Weekly Soda Consumption	6.779	6.783	5.9	6.087	5.457	4.899
	(7.870)	(8.142)	(7.364)	(7.471)	(6.902)	(6.269)
Weekly Intensive Exercise	3.796	4.034	3.562*	3.994	3.594	3.906
	(2.042)	(2.109)	(1.930)	(2.013)	(1.715)	(1.836)
Maternal Education (years)	12.020*	12.591	13.153*	14.072	13.832*	15.142
	(3.228)	(3.141)	(2.644)	(2.764)	(3.150)	(2.699)
Family Income (log)	10.170*	10.376	10.486*	10.834	10.574*	11.046
	(0.828)	(0.982)	(0.814)	(0.845)	(0.905)	(0.855)

Attending Public School	0.899	0.834	0.837	0.775	0.862*	0.711
	(0.302)	(0.372)	(0.370)	(0.418)	(0.346)	(0.454)
Reading Scores at Kindergarten	25.514	26.005	28.336*	31.023	34.052*	36.964
	(6.251)	(6.376)	(8.327)	(9.017)	(13.689)	(12.555)
Observations	307	609	190	550	138	661

Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data
Note: * $p<0.05$.

Table 12.Heterogeneous effects of obesity on reading scores from quantile regression models with bootstrapped standard errors in case-complete sample

Quantile:	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Model 1: Baseline[a]	-0.422***	-0.203**	-0.128**	-0.116**	-0.077*	-0.106***	-0.076*	-0.006	-0.021
	-0.134	-0.1	-0.052	-0.048	-0.046	-0.038	-0.042	-0.028	-0.024
Model 2: + Parental Expectation[b]	-0.361***	-0.221***	-0.159***	-0.107**	-0.049	-0.062*	-0.04	-0.025	-0.007
	-0.137	-0.066	-0.059	-0.053	-0.041	-0.037	-0.034	-0.031	-0.03
Model 3: + Behavioral Problems[c]	-0.226	-0.148*	-0.115**	-0.061	-0.046	-0.065	-0.018	-0.027	0.001
	-0.16	-0.085	-0.059	-0.059	-0.048	-0.045	-0.039	-0.036	-0.024
Model 4: +Work Habit[d]	-0.153	-0.082	-0.087	-0.101	-0.056	-0.02	-0.043	-0.015	-0.019
	-0.105	-0.094	-0.061	-0.071	-0.061	-0.049	-0.043	-0.038	-0.035
Model 5: +School Absence[e]	-0.163	-0.083	-0.082	-0.095*	-0.048	-0.025	-0.029	-0.005	-0.012
	-0.115	-0.098	-0.06	-0.051	-0.04	-0.041	-0.041	-0.041	-0.033

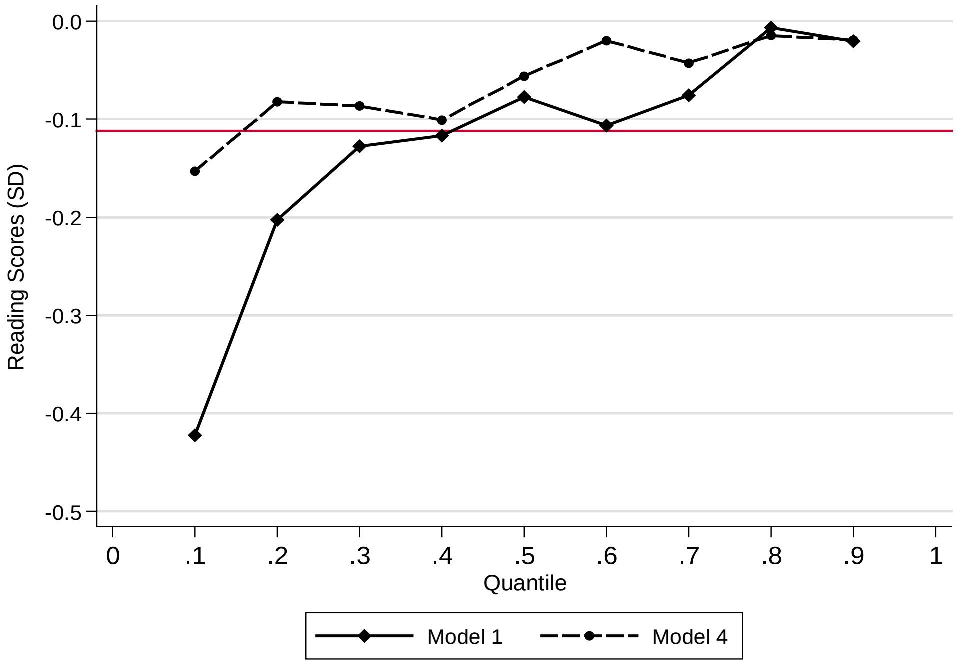
Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data
Note:
[a] Model 1 includes obesity, age, gender, birth weight, tv viewing (hours), soda consumption, intensive activity, maternal education, family income (log), public school, and reading IRT scores at kindergarten.
[b] Model 2 includes measures in Model 1, plus parental educational expectation (less than college).
[c] Model 3 includes measures in Model 2, plus internalizing behavioral problems
[d] Model 4 includes measures in Mode l3, plus approaches to learning.
[e] Model 5 includes measures in Model 4, plus total days of missing schools.
*p≤ 0.05; **p≤ 0.01; *** p≤ 0.001.

Table 13.Heterogeneous effects of obesity on math scores from quantile regression models with bootstrapped standard errors in case-complete sample

Quantile:	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Model 1: Baseline[a]	-0.219*	-0.068	-0.088	-0.062	-0.037	-0.061*	-0.086***	-0.086***	-0.078**
	-0.131	-0.077	-0.053	-0.05	-0.054	-0.036	-0.032	-0.031	-0.032
Model 2: + Parental Expectation[b]	-0.215*	-0.087	-0.079	-0.033	-0.052	-0.087**	-0.062	-0.068**	-0.043*
	-0.121	-0.071	-0.062	-0.063	-0.056	-0.043	-0.041	-0.027	-0.025
Model 3: + Behavioral Problems[c]	-0.019	0.005	-0.05	0.009	-0.019	-0.039	-0.053	-0.075**	-0.022
	-0.124	-0.061	-0.05	-0.062	-0.056	-0.037	-0.038	-0.037	-0.027
Model 4: +Work Habit[d]	-0.005	0.079	-0.027	-0.019	0.034	-0.032	-0.016	-0.019	-0.039
	-0.138	-0.076	-0.054	-0.058	-0.056	-0.046	-0.038	-0.046	-0.031
Model 5: +School Absence[e]	-0.017	0.038	-0.007	-0.014	0.01	-0.04	-0.035	-0.029	-0.033
	-0.181	-0.089	-0.057	-0.041	-0.038	-0.048	-0.046	-0.054	-0.037

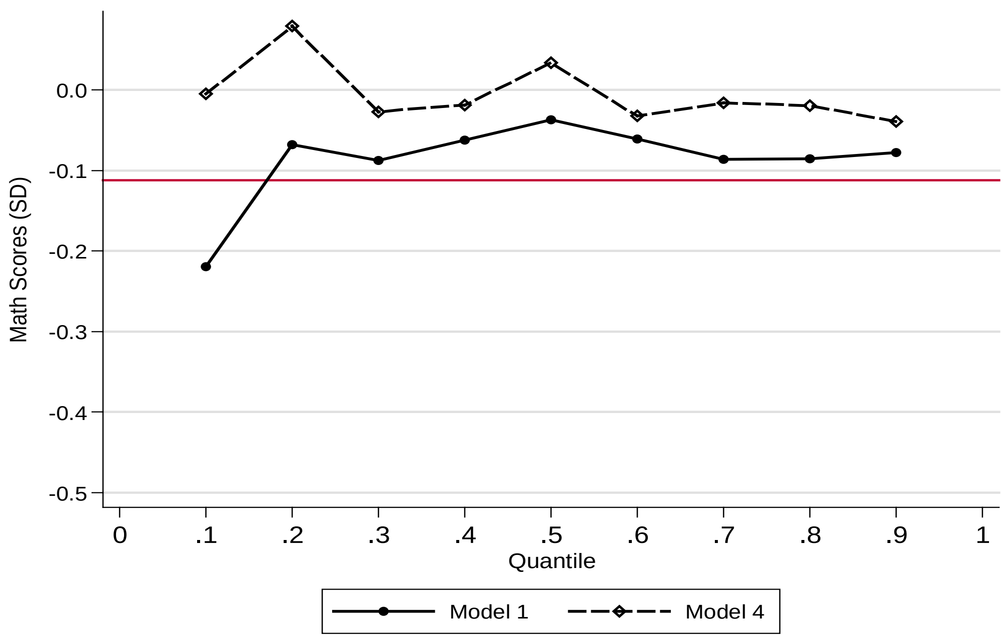
Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data
Note:
[a] Model 1 includes obesity, age, gender, birth weight, tv viewing (hours), soda consumption, intensive activity, maternal education, family income (log), public school, and reading IRT scores at kindergarten.
[b] Model 2 includes measures in Model 1, plus parental educational expectation (less than college).
[c] Model 3 includes measures in Model 2, plus internalizing behavioral problems
[d] Model 4 includes measures in Mode l3, plus approaches to learning.
[e] Model 5 includes measures in Model 4, plus total days of missing schools.
*p≤ 0.05; **p≤ 0.01; *** p≤ 0.001.

Figure 4. Heterogeneous effect of obesity on reading scores for White students



Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data

Figure 5. Heterogeneous effect of obesity on math scores for White students



Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data

Appendices

Table A9. Heterogeneous effects of obesity on reading scores from quantile regression models with bootstrapped standard errors in imputed sample

Quantile:	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Model 1: Baseline[a]	-0.317*	-0.201*	-0.139*	-0.114*	-0.074	-0.090*	-0.066*	-0.026	-0.023
	-0.11	-0.088	-0.057	-0.047	-0.045	-0.04	-0.033	-0.037	-0.024
Model 2: + Parental Expectation[b]	-0.289*	-0.184*	-0.154*	-0.125*	-0.085	-0.069	-0.051	-0.033	-0.018
	-0.097	-0.076	-0.064	-0.055	-0.054	-0.048	-0.038	-0.033	-0.028
Model 3: + Behavioral Problems[c]	-0.18	-0.163	-0.132*	-0.083	-0.069	-0.045	-0.036	-0.026	-0.007
	-0.106	-0.08	-0.06	-0.054	-0.037	-0.037	-0.036	-0.027	-0.026
Model 4: +Work Habit[d]	-0.119	-0.119	-0.107*	-0.085	-0.048	-0.039	-0.048	-0.019	-0.011
	-0.095	-0.066	-0.045	-0.05	-0.046	-0.037	-0.034	-0.033	-0.028
Model 5: +School Absence[e]	-0.122	-0.117	-0.109	-0.086	-0.051	-0.04	-0.044	-0.018	-0.008
	-0.088	-0.072	-0.051	-0.055	-0.045	-0.039	-0.031	-0.032	-0.03

Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data
Note:
[a] Model 1 includes obesity, age, gender, birth weight, tv viewing (hours), soda consumption, intensive activity, maternal education, family income (log), public school, and reading IRT scores at kindergarten.
[b] Model 2 includes measures in Model 1, plus parental educational expectation (less than college).
[c] Model 3 includes measures in Model 2, plus internalizing behavioral problems
[d] Model 4 includes measures in Mode l3, plus approaches to learning.
[e] Model 5 includes measures in Model 4, plus total days of missing schools.
*p≤ 0.05; **p≤ 0.01; *** p≤ 0.001.

Table A10. Heterogeneous effects of obesity on math scores from quantile regression models with bootstrapped standard errors in imputed sample

Quantile:	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Model 1: Baseline[a]	-0.220*	-0.11	-0.086	-0.048	-0.034	-0.036	-0.053	-0.071*	-0.074*
	-0.111	-0.076	-0.051	-0.053	-0.048	-0.041	-0.038	-0.029	-0.031
Model 2: + Parental Expectation[b]	-0.206*	-0.111	-0.084	-0.035	-0.052	-0.056	-0.062	-0.05	-0.053
	-0.11	-0.068	-0.057	-0.052	-0.045	-0.045	-0.039	-0.03	-0.032
Model 3: + Behavioral Problems[c]	-0.082	-0.061	-0.07	-0.024	-0.017	-0.041	-0.042	-0.046	-0.028
	-0.12	-0.072	-0.054	-0.056	-0.042	-0.033	-0.037	-0.033	-0.033
Model 4: +Work Habit[d]	-0.059	0.003	-0.025	-0.021	0.005	-0.036	-0.025	-0.039	-0.035
	-0.1	-0.073	-0.049	-0.048	-0.044	-0.037	-0.033	-0.033	-0.028
Model 5: +School Absence[e]	-0.055	0.017	-0.017	-0.022	0.009	-0.025	-0.023	-0.032	-0.029
	-0.099	-0.07	-0.053	-0.05	-0.039	-0.038	-0.033	-0.038	-0.033

Source: The Earl Childhood Longitudinal Study-Kindergarten to Eighth Grade Public-use Data
Note:
[a] Model 1 includes obesity, age, gender, birth weight, tv viewing (hours), soda consumption, intensive activity, maternal education, family income (log), public school, and reading IRT scores at kindergarten.
[b] Model 2 includes measures in Model 1, plus parental educational expectation (less than college).
[c] Model 3 includes measures in Model 2, plus internalizing behavioral problems
[d] Model 4 includes measures in Mode l3, plus approaches to learning.
[e] Model 5 includes measures in Model 4, plus total days of missing schools.
*p≤ 0.05; **p≤ 0.01; *** p≤ 0.001.