January 2017

Demographic Differences In The Causal Effects Of Obesity Status On Child Academic Achievement

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DEMOGRAPHIC DIFFERENCES IN THE CAUSAL EFFECTS OF OBESITY STATUS ON CHILD ACADEMIC ACHIEVEMENT

by

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Bachelor of Arts, Ohio State University, 2013

A Thesis

Submitted to the Graduate Faculty

of the

University of North Dakota

in partial fulfillment of the requirements

for the degree of

Master of Science in Applied Economics

Grand Forks, North Dakota

May
2017

This thesis, submitted by Yoshie Hayasaka Kim in partial fulfillment of the requirements for the Degree of Master of Science in Applied Economics from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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Department	Applied Economics
Degree	Master of Science

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Yoshie Hayasaka Kim
March 25, 2017

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ACKNOWLEDGEMENTS

I wish to express my sincere appreciation to the Applied Economics faculty and to the members of my advisory committee for their guidance and support during my time in the master's program at the University of North Dakota.

ABSTRACT

Many studies have found a negative correlation between obesity and academic achievement; however, determining and reaching a consensus about the nature of causality between these two variables have posed a challenge for scholars and researchers. If obesity does indeed have a negative causal effect on academic achievement, it has significant policy implications as it affects human capital investment. In this paper, I use the National Longitudinal Study of Youth-1979, Child and Young Adult data and estimate OLS, FE, traditional IV, and Lewbel IV models for children ages 5-12, stratified by race and gender. Under an individual fixed-effects model, I find that there are statistically significant, negative effects of being overweight for non-Hispanic/non-black boys, and of being obese for Hispanic/black girls on reading test scores. On the other hand, there seems to be a positive effect of being obese for Hispanic/black boys, though not at conventional levels. These results show the importance of stratifying the study population, not only by gender, but by race when studying obesity effects on academic achievement.

I. Introduction

With American youth struggling to meet state academic standards and trailing behind their counterparts from other developed nations, there has been an increasing push for education reform in the United States. Stricter teacher assessments, increased school choice through charter schools and vouchers, and state required testing are some of the ways in which governments have attempted to increase student academic outcomes. However, although structural reform of the education system is paramount, there are other factors that often get overlooked when addressing this problem. One of them is the effects of student health on student academic outcomes. In this paper, I will focus on one aspect of health—obesity, and its effect on student test scores.

In the past 30 years, childhood obesity has more than doubled in children and quadrupled in adolescents in the U.S., with more than one third of children and adolescents overweight or obese in 2012 (Center for Disease Control). Obesity and its association with increased risks of health conditions (e.g. asthma, menstrual abnormalities, sleep apnea, type 2 diabetes) are well-known. However, what often gets overlooked is the potential negative impacts that obesity can have on academic achievement, which may lead to long-term consequences. Research have shown that cognitive skills in childhood are important determinants of educational attainment and social and economic success in adulthood (Heckman 2006). Thus, establishing the causal link (or lack thereof) between obesity and academic achievement in childhood is important in assessing the effectiveness of policies and programs focusing on early intervention for the purpose of human capital investment.

There are three main suggested hypotheses as to why and how childhood obesity may negatively affect academic achievement. The first is that poor health (caused by or concurring with obesity) can lead to more absences from school. Stress and difficulty getting quality sleep may reduce a child's ability to concentrate in school, thus resulting in lower academic performance. (See Geier et al., 2007 for discussion on absences; Redline et al., 1999 for discussion on sleeping disorders). The second hypothesis is that being obese may increase the likelihood of getting teased, bullied, and discriminated by peers and/or teachers, causing psychosocial problems which may affect character development, thus affecting the child's learning and cognitive development (Puhl & Latner, 2007). Third, biology and genetics may play a role in obesity and cognitive achievement by affecting brainpower at the cellular level. (Gunstad et al., 2008; Taki et al., 2008) On the other hand, it is also possible that obesity can have a positive effect on academic achievement, as students redirect their use of time from physical recreational activities to studying (Eide et al. 2010).

The biggest challenge in determining the causal relationship between obesity and academic achievement comes from the issue of endogeneity. Obesity may be correlated with a host of latent variables, such as family and environmental factors, that may also impact academic achievement. There is also the possibility that causality runs not only from weight status to academic achievement, but the other way around. Endogeneity may also arise from measurement error, which may be a problem in survey data. Conclusions from past research on the causal effect of obesity on academic achievement have been inconsistent.

Determining the nature of the causal relationship between obesity and academic achievement can shed a greater light on the importance of governments and institutions to tackle the obesity problem, not just for health reasons and its associated social costs, but also to promote greater student achievement and human capital investment.

II. Literature Review

There have been a number of studies investigating the relationship between child obesity and academic performance. In an OLS specification, many studies find a negative relationship between obesity and academic/cognitive performance (e.g. Davis & Cooper, 2011). However, when exploring whether a causal relationship exists, the findings are not entirely consistent with each other.

Datar and Sturm (2006) use data from the Early Childhood Longitudinal Study – Kindergarten (ELCS-K) and employ multivariate, school level random effects regression models and find that becoming overweight from kindergarten to 3rd grade leads to adverse academic achievement and social-behavioral outcomes for girls, but not boys. Zavodny (2013) also uses the ELCS-K data (with data from two additional waves) and find that obesity is more negatively related to teacher assessments of academic performance than to test scores under a child fixed effects specification.

Sabia (2007) uses data from the National Longitudinal Study of Adolescent Health (Add Health) and employs an individual fixed effects model, instrumental variables estimation using parental BMI as an instrument, and the Lewbel IV estimation. He finds a negative relationship between BMI and GPA for white females aged 14-17. Fletcher and Lehrer (2008), in their working paper, use the same dataset but find no statistically significant effect of obesity on academic achievement when employing family fixed effects and a FEIV approach using genetic markers as instruments.

Averett and Stifel (2007) and Kaestner and Grossman (2009) both look at data from the National Longitudinal Survey of Youth – 1979, Children and Young Adults (NLSY79 Child/YA) and reach different conclusions. Averett and Stifel (2007) use FE, IV, and Lewbel IV estimations. They find that for children ages 6-13, being overweight leads to lower reading scores under a FE model, and to lower reading and math scores when employing an IV estimation using mother's historic BMI as an instrument and the Lewbel IV estimation. Averett and Stifel (2010) revisit this topic in a subsequent paper and analyze the effects of being overweight stratified by race and gender. They find that overweight white boys have math and reading scores approximately one standard deviation lower than the mean. They also find that overweight white girls have lower math scores and overweight black boys and girls have lower reading scores. On the other hand, Kaestner and Grossman (2009) find no effect of obesity on test scores for ages 5-12 under a first difference and FD-IV model.

Palermo and Dowd (2012) also find no evidence of a negative association between obesity and cognitive ability for children ages 5-19 under an individual fixed effects specification, using the Children Development Supplement of the Panel Survey of Income Dynamics.

The above-mentioned studies have all used nationally-representative data of children in the United States in examining the relationship between obesity and academic/cognitive outcomes. There are other studies that have explored this relationship using data from other countries or within a certain region of the United States. The results here, are also very mixed.

Cho et al. (2009) look at the relationship between academic achievement and obesity in South Korea by using a simultaneous probit-linear regression model and find evidence for negative, mutual causality. Black et al. (2015) use longitudinal data from Australia and find a negative effect of obesity on academic outcomes for boys in grades 3-7 but not for girls, contrary to most findings of negative associations for girls (Datar & Sturm, 2007; Sabia, 2007). Ding et al. (2009) use data from high school students in northern Virginia and use genetic markers as

IVs. They find that obesity leads to a 0.45 point decrease in GPA for female students but not male. Scholder et al. (2009) also use genetic markers as IVs but find no evidence that body weight affects academic performance for children born in Avon of England at the age of 14.

Although this is not an exhaustive review of literature on the topic, it is clear how determining and coming to a consensus about the nature of causality between obesity and academic achievement have posed a challenge for scholars and researchers. Some reasons why the findings of previous studies differ may be due to the differences in choice of geographic location, age of the study population, control variables, differing measures of academic achievement, and empirical methods (Black et al. 2015). In addition, instruments that are commonly chosen in IV models, such as past parental BMI and children's lagged weight categories, may not meet the assumptions of a valid instrument (Scholder et al. 2009). Scholder et al. (2009) suggest that the usage of genetic markers as instruments is appropriate; however, studies that use genetic markers as instruments also reach different conclusions (e.g. Ding et al. 2009; Scholder et al. 2009). Given the inconsistencies of findings in previous literature, this is a topic that still needs much further investigation.

I wish to build upon previous literature by expanding upon the work done by Kaestner and Grossman (2009) and Averett and Stifel (2007, 2010). I will be using the same dataset that they have used, the children and young adult data from the National Longitudinal Survey of Youth-1979 (NLSY79 Child Y/A). (Description of data presented below in Section IV). My data, however, will have data up to the year 2012, which will allow for the inclusion of more observations. Furthermore, I will look at the effects of obesity of academic achievement stratified by gender and race of the child. Other researchers have found that obesity effects on academic outcomes differ by race (e.g. Sabia 2007). Kaestner and Grossman did not look at obesity effects separately by racial group. While Averett and Stifel (2010) did study race effects of obesity on cognitive ability, they only used data from the NLSY79 Child Y/A up until 2002. They also dropped approximately 20% of the observations that had height and weight measurements reported by the mother. If these dropped observations are not random, the results may be biased. In this paper, instead of dropping cases with parent-reported measurements, I attempt to correct for reporting bias by using Cawley and Burkhauser's (2006) method. Thus, I wish to expand upon the work that Kaestner and Grossman (2009) and Averett and Stifel (2007, 2010) have done by seeing whether there are differences in obesity effects depending on the child's gender and race, while correcting for parent-reporting bias and adding five additional waves of data through 2012.

III. Empirical Framework

Ordinary Least Squares Model

I will begin my analysis of the effect of weight status on child academic achievement by estimating an Ordinary Least Squares regression with the following equation:

$$A_{it} = \alpha + X_{it}'\beta + BW_{it}'\gamma + \varepsilon_{it},$$

where A_{it} is a measure of academic achievement for child *i* at time *t*, X_{it} is a vector of individual-level, family-level, and community-level observable characteristics, and BW_{it} is a measure of the child's bodyweight. Bodyweight enters the equation as a set of dummy variables indicating whether the child is underweight, overweight, or obese. The vector of parameters of interest is γ.

The OLS estimator will give us an idea of how much the raw relationship between obesity and academic achievement can be explained by observed characteristics. It is important to remember that OLS estimates are unbiased only if obesity status is exogenous and that there are no unobserved child, family, and community characteristics that are correlated with weight status and academic achievement. In other words, $E(\varepsilon|X, BW) = 0$. When there are unobserved characteristics present, the OLS model suffers from unobserved heterogeneity. In addition, for OLS estimates to be unbiased, causality must run from weight status to academic achievement and not the other way around. When there is reason to believe that causality runs in both directions, the model suffers from simultaneity, giving biased estimates.[1]

Fixed Effects Model

In analyzing the effects of obesity on academic achievement, there are numerous latent family and environmental factors that may play a role, resulting in unobserved heterogeneity, or omitted variable bias, under an OLS specification. The second model used in my analysis, the fixed effects model, removes this bias by focusing on within-child variation. This model controls for time-invariant unobserved heterogeneity. Factors such as a child's discipline and other psychological and/or physical aspects that are unobservable to the researcher are controlled for.

[1] Another source of endogeneity is measurement error. These include coding and reporting errors in the data. Extensive effort was made to remove these types of errors in the data by dropping observations where measurements were beyond the range of accepted values (e.g. 0 to 12 for inches), correcting for parent-reporting bias for mother-reported height and weight measurements by using Cawley and Burkhauser's (2006) method (See Section IV for details), and dropping biologically implausible values (BIV) for BMI as defined by the Center for Disease Control. BIV for BMI are those with z-scores below -4 and above +8. (Note: CDC increased the upper BIV cutoff point from +5 to +8 for BMI z-scores in 2016 based on analyses of 2 to 18 year olds in the National Health and Nutrition Examination Survey (NHANES) 1999-2000 through 2011-2012, and 2 to 4 year olds in CDC's Pediatric Nutrition Surveillance System (PedNSS).)

It also further controls for unobservable family characteristics, such as parental and sibling interactions with the child.[2] The fixed effects equation thus becomes:

$$A_{it} = \alpha + \mu_i + X_{it}'\beta + BW_{it}'\gamma + \varepsilon_{it},$$

Where μ_i is a child-specific dummy variable. In the above equation, X_{it} now only includes individual-level, family-level, and community-level characteristics that are not fixed over time. Year dummies are also included to control for a time trend. All time-invariant variables drop out of the equation.

Although a fixed effects model can address the problem of unobserved heterogeneity, it is important to note that this model does not control for any time-varying unobserved factors that are associated with weight and academic achievement, such as a changes in a child's motivation, attitude, or peer groups. If such time-varying unobserved factors exist, fixed effects estimates are biased.

Instrumental Variables

One caveat of the fixed effects model is that although it addresses the problem of unobserved heterogeneity, it does not address the endogeneity issue arising from reverse causality or simultaneity. An obese child may perform poorly in school due to various psycho-social pathways, but at the same time, a child who performs poorly in school may cope by eating excessively or not maintaining a healthy lifestyle, thus leading to weight gain.

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[2] Another way the literature has addressed the issue of unobserved family characteristics is by estimating sibling fixed effects models. Averett and Stifel (2007) estimated such a model and state that the results were qualitatively similar to their individual fixed effects models. The motivation of estimating sibling fixed effects comes from the argument that differences between siblings remove variance in weight that may be attributed to shared family environment. However, Cawley (2004) argues that family environments explain only a small proportion of the variance in weight across siblings, making it an inappropriate way to remove unobserved heterogeneity.

The most common way of addressing the issue of endogeneity is using instrumental variables. In an instrumental variables approach, instrumental variable(s) Z are used to isolate movements in X that are uncorrelated with the error term u to produce consistent coefficient estimates. A valid instrumental variable must satisfy the conditions of instrument relevance and instrument exogeneity. In other words, the instrument(s) must be uncorrelated with the error term, directly affect the endogenous variable, in this case, BW (weight status), but only affect the dependent variable, A (academic achievement), *indirectly* through its relationship with the endogenous variable, BW.

The problem with this approach is in its difficulty in identifying valid instrument(s). In studying the causal effects of obesity on academic achievement, instruments used in past literature include historical parental BMI (e.g. Sabia, 2007; Averett & Stifel, 2007) and child's past weight status (Kaestner & Grossman, 2007). However, these instruments may not fully satisfy the conditions of a valid IV. Scholder et al. (2009) point out that the correlation between a child' past and current weight can be as high as 0.95, which suggests that a child's earlier weight is almost a perfect predictor for his or her current weight, which raises doubts about its use as an IV. They also argue that past maternal weight is likely to be correlated with the family environment, which is also an important determinant in the child education production function, thus violating the condition of exclusion restriction.[3] In this paper, I present IV estimation results

[3] Lindeboom et al. (2010) exploit the rich data from the British National Child Development Study (NCDS) to conduct a number of checks for the appropriateness of using parental weight as an instrument. Findings suggest that genetic factors are the main contributors to intergenerational association of obesity. They also look at adopted children and find that environmental factors play only a small role in predicting obesity. However, as Lindeboom et al. states, parental weight as instruments will only be valid if the same genes that predict obesity do not predict (in our case) educational achievement. Furthermore, they point to another study that finds that family environment plays the main role in the development of children's food preferences, which may affect their health and weight.

using mother's BMI in 1985, similar to what Averett and Stifel (2007) have done, for the purpose of comparing results with previous literature.[4]

Lewbel IV Estimation

Given how difficult it is to identify a valid instrument in analyzing the causal effects of obesity on academic achievement, an alternative method is to use the Lewbel IV estimation. This estimation may be useful in cases where conventional instruments are not available or are weak. The Lewbel approach (2012) is explained below: Let

$$Y_1 = X'\beta_1 + Y_2\gamma_1 + \varepsilon_1, \qquad \varepsilon_1 = \alpha_1 U + V_1,$$

$$Y_2 = X'\beta_2 + \varepsilon_2, \qquad \varepsilon_2 = \alpha_2 U + V_2,$$

where Y_1 is academic achievement and Y_2 is body weight status. *U* is an omitted variable or other unobserved factor that may directly influence both Y_1 and Y_2, while V_1 and V_2 are idiosyncratic errors in the equations. *U,* V_1, and V_2 are uncorrelated with *X* and are conditionally uncorrelated with each other, conditioning on *X*. Let *Z* be a vector of observed exogenous variables, which could be a subvector of *X* or equal to *X*. Then, $[Z - \bar{Z}]\varepsilon_2$ can be used as an instrumental variable with key additional conditions that

$$E(X\varepsilon_1) = 0, \qquad E(X\varepsilon_2) = 0, \qquad cov(Z, \varepsilon_1, \varepsilon_2) = 0,$$

and that there is some heteroskedasticity in ε_j. Lewbel (2012) states that these are standard assumptions, except the condition of requiring heteroscedasticity. Identification is achieved by having regressors that are not correlated with the covariance of the heteroskedastic errors. The

[4] Averett and Stifel (2007) use maternal BMI in 1981 as instruments. In this paper, maternal BMI in 1985 is used as instruments, as choosing this particular year guarantees that even the youngest of all respondents would have turned at least the age of 20, which would classify them as being an "adult" when calculating weight categories based on BMI percentiles.

above mentioned instrument can then be used in 2SLS to estimate the IV regression, just as in the case with using conventional instruments.[5]

Lewbel does point out that identification in this method is based on higher moments and are thus more likely to give noisier and less reliable estimates than identification based on standard exclusion restrictions. However, in cases where conventional instruments are weak or nonexistent, this estimation method may prove to be very useful. In studying the causal effects of obesity on academic achievement, traditional instruments used in previous literature, such as past parental weight and lagged child weight status, may not fully satisfy the exclusion restrictions necessary for a valid IV. Hence, using the Lewbel IV estimation for this study may be appropriate.

IV. Data

In this paper, I will use data from the National Longitudinal Survey of Youth-1979, Children/Young Adult (NLSY79 Child/YA), which is a longitudinal study that follows the biological children of the women in the NLSY79 cohort. The NLSY79 follows a sample of American youth born between 1951 and 1964, with an oversampling of black, Hispanic, and low-income white populations. The original cohort consisted of 12,686 respondents between the ages of 14 and 22 at the 1979 Wave I interview. The biological children of women in the NLSY79 were interviewed for the first time in 1986 with their ages at the time of interview

[5] The endogenous variable in this study is weight status, which consist of binary dummy variables. In his paper, Lewbel (2012) does not explicitly assume that Y_2 is continuous, but does not show that the identifying assumptions can be satisfied when Y_2 is not continuous. Hence, in a working paper, Lewbel (2016) shows that the assumptions required for Lewbel's estimator can be satisfied when an endogenous regressor is binary. He thus argues that existing implementations of the estimator, such as IVREG2H in STATA, can be applied with a binary endogenous variable.

ranging from 0 to 23 years old. Interviews and assessments were conducted biennially to follow the cognitive, physical, and socio-emotional development of these children. At the time of the 2012 interviews, there were 11,512 children born to women of NLSY79. My analysis will use data through 2012, the most current year available.

Academic achievement is measured by the Peabody Individual Assessment Test (PIAT) math, reading recognition, and reading comprehension scores. The PIAT assessments are administered to children ages 5 and up. It is an assessment of academic achievement with high test-retest reliability and concurrent validity (NLS BLS). The PIAT math assessment begins with early skills such as recognizing numerals, and progresses to advanced concepts in geometry and trigonometry. The PIAT reading recognition assessment measures word recognition and pronunciation ability, which are essential components of reading achievement. The PIAT reading comprehension assessment measures a child' ability to derive meaning from sentences that are read silently.

To study the effects of weight, I use height and weight data of children between the ages of 5 and 12, the typical ages of children in elementary school (grades K to 6). Child BMI was calculated using the following formula:

$$BMI = \frac{Weight\ (lb)}{[Height\ (in)]^2} \times 703$$

Children were then categorized into weight categories defined by the BMI-for-age growth charts from the Center for Disease Control, using the *zanthro* module in Stata (just as Black et al 2015 have done). Those with BMI percentiles of less than the 5^{th} percentile are categorized as underweight, from the 5^{th} to less than the 85^{th} percentile as normal weight, 85^{th} to less than the 95^{th} percentile as overweight, and equal to or greater than the 95^{th} percentile as obese. BMI percentiles express a child's BMI in comparison to children in the U.S. who participated in national surveys that were conducted from 1963-1965 to 1988-1994 (CDC).

Child height and weight data was taken from the child supplement. In cases where height and weight measurements were missing from the child supplement, measurements from the mother supplement, which was administered starting in 2006, were used. Approximately 69% of height data and 65% of weight data in the child supplement were obtained by the interviewer using a tape measure and/or a scale. All other height and weight measurements, excluding the 2-3% recalled by the child, are measurements reported by the mother. This may raise some concerns, as there have been studies that found that parent-reported height and weight measures are often times biased, with underreporting of height at younger ages, especially for low-income children (Weden et al. 2013). Such underreporting of height will bias upwards the prevalence of obesity in younger age groups due to the squaring of height in calculating BMI. In this paper, I attempt to correct reporting bias by using Cawley and Burkhauser's (2006) proposed method of predicting height and weight based on models estimated from the National Health and Nutrition Examination Survey (NHANES III).

Data from NHANES III contain parent-reported (for children age 12 and under), self-reported (for individuals above the age of 12), and actual height and weight measurements. Cawley and Burkhauser (2006) regress actual weight on reported weight, its square, and on age and its square, separately by race and gender. The coefficients from the regressions can then be transferred to another dataset and multiplied by the self-reported values to construct measures of weight and height that are corrected for reporting error. Although Cawley and Burkhauser provide their coefficient estimates in their paper, the data they used from NHANES III only includes individuals age 12 and up, who gave self-reported weight and height measurements.

The age group that is the focus of my paper is ages 5 to 12. What I am interested in is not self-reporting bias, but parent-reporting bias. Hence, instead of utilizing the coefficients provided in their paper, I use their method to estimate coefficients by using data from NHANES III that only includes children aged 12 and under with parent-reported height and weight measurements.

Table 1A and 1B show the estimated coefficients from this model. The R squared values are quite high, with values between 0.94 and 0.96 for the weight and height models. One assumption that we need to make, however, is that of "transportability"—that the relationship between parent-reported height/weight and measured height/weight are the same in the NHANES and the NLSY. In the process of cleaning data, I also dropped observations where the calculated BMI fell in the Biologically Implausible Values (BIV), as defined by the CDC.[6]

Table 1A – Estimated Coefficients from NHANES III to Correct for Parent-Reporting Bias of Height

	Black Male	Hispanic Male	Non-Black, Non-Hispanic Male	Black Female	Hispanic Female	Non-Black, Non-Hispanic Female
Reported Height	0.3384	-0.3278	-0.4655	-0.3630	-0.2440	-0.4302
Reported Height Squared	0.0052	0.0063	0.0075	0.0042	0.0051	0.0073
Age in Years	2.8412	2.9559	3.4725	4.0027	2.9486	3.0813
Age in Years Squared	-0.0444	-0.0820	-0.1208	-0.1253	-0.0717	-0.0845
Constant	36.1113	34.3703	36.4639	35.2374	32.6846	35.8658
R squared	**0.95**	**0.94**	**0.95**	**0.95**	**0.94**	**0.95**

Table 1B – Estimated Coefficients from NHANES III to Correct for Parent-Reporting Bias of Weight

	Black Male	Hispanic Male	Non-Black, Non-Hispanic Male	Black Female	Hispanic Female	Non-Black, Non-Hispanic Female
Reported Weight	0.7239	0.3523	0.5480	0.6571	0.4410	0.4828
Reported Weight Squared	0.0012	0.0032	0.0021	0.0018	0.0028	0.0025
Age in Years	1.4080	2.5317	2.0594	2.2073	2.4117	1.6849
Age in Years Squared	-0.0180	-0.0462	-0.0290	-0.1092	-0.0290	0.0292
Constant	4.2565	11.5054	7.7306	5.1948	9.0396	9.6338
R squared	**0.96**	**0.94**	**0.95**	**0.94**	**0.94**	**0.95**

[6] Biologically implausible values (BIV) for BMI are those with z-scores below -4 and above +8. (Note: CDC increased the upper BIV cutoff point from +5 to +8 for BMI z-scores in 2016 based on analyses of 2 to 18 year olds in the NHANES 1999-2000 through 2011-2012, and 2 to 4 year olds in CDC's Pediatric Nutrition Surveillance System (PedNSS).

Table 2A – Mean Test Scores by Race, Age, and Weight Status for Boys

	All	Underweight	Normal Weight	Overweight	Obese
		0-5%	5-85%	85-95%	95-100%
Non-Hispanic, Non-Black Males					
Ages 5-6					
PIAT-Math	17.3	17.3	17.6	17.4	16.0***
PIAT-Reading Comprehension	17.0	17.1	17.3	17.2	15.9***
PIAT-Reading Recognition	18.0	17.8*	18.2	18.1	17.0*
Ages 7-8					
PIAT-Math	33.8	31.9**	34.1	34.2	34.3
PIAT-Reading Comprehension	32.7	30.1***	33.0	32.6	33.1
PIAT-Reading Recognition	34.9	32.4	35.4	34.7	35.1
Ages 9-10					
PIAT-Math	47.7	45.6*	47.8	48.5	48.0
PIAT-Reading Comprehension	44.2	44.1	43.9	45.1	44.2
PIAT-Reading Recognition	48.3	47.2	48.2	49.5	48.0
Ages 11-12					
PIAT-Math	55.5	51.0***	55.7	56.0	55.3
PIAT-Reading Comprehension	52.2	47.9**	52.3	51.9	53.2
PIAT-Reading Recognition	58.1	51.9	58.3	58.5	58.5
Hispanic and Black Males					
Ages 5-6					
PIAT-Math	13.9	13.6	13.6	15.2***	14.7**
PIAT-Reading Comprehension	15.7	15.3	15.3	15.6	16.3**
PIAT-Reading Recognition	16.3	15.7	15.9	16.4	17.0**
Ages 7-8					
PIAT-Math	27.7	26.5	27.6	29.3**	28.7
PIAT-Reading Comprehension	28.3	27.1	28.2	30.0**	28.6
PIAT-Reading Recognition	30.7	30.3	30.3	32.8***	31.7*
Ages 9-10					
PIAT-Math	40.6	37.8	40.6	41.8	41.8*
PIAT-Reading Comprehension	38.5	36.7**	38.0	39.8**	39.6**
PIAT-Reading Recognition	42.1	40.6	41.5	43.5**	44.0***
Ages 11-12					
PIAT-Math	47.9	48.0	47.5	48.6	48.9**
PIAT-Reading Comprehension	44.8	45.4	44.3	45.6*	45.8*
PIAT-Reading Recognition	50.2	50.5	49.5	51.5**	51.2*

* Estimate is statistically different from estimate for normal weight children at the 0.10 level

** Estimate is statistically different from estimate for normal weight children at the 0.05 level

*** Estimate is statistically different from estimate for normal weight children at the 0.01 level

Values are rounded to the nearest tenth decimal

Table 2A and 2B show descriptive statistics showing the mean test scores of children ages 5-12 by race[7], age, and weight status. Interestingly, Hispanic and black boys who are

[7] "Non-black/Non-Hispanic" include those whose race was coded "white" or "other." Asians, Native Americans, and Pacific Islanders were coded as "other" and is thus included in this group.

overweight or obese have higher mean test scores than those who are normal weight. (See Table 2A). For non-Hispanic, non-black (henceforth white) boys, there is a negative relationship between obesity and test scores for ages 5-6. Underweight status has a greater negative relationship with test scores than obese status. There is also very little correlational effects of obesity on test scores for girls as well, with the test score means of obese girls statistically different from that of normal weight girls only at ages 11 and 12 (Table 2B).

Table 2B – Mean Test Scores by Race, Age, and Weight Status for Girls

	All	Underweight	Normal Weight	Overweight	Obese
		0-5%	5-85%	85-95%	95-100%
Non-Hispanic, Non-Black Females					
Ages 5-6					
PIAT-Math	17.3	15.4***	17.4	18.1	18.4*
PIAT-Reading Comprehension	18.0	16.7**	18.2	18.8	18.4
PIAT-Reading Recognition	18.8	17.3**	18.9	19.7	19.0
Ages 7-8					
PIAT-Math	33.4	31.1**	33.4	34.9**	33.9
PIAT-Reading Comprehension	34.1	32.9	34.3	34.4	34.1
PIAT-Reading Recognition	36.6	35.2	36.7	37.3	36.8
Ages 9-10					
PIAT-Math	46.2	44.2**	46.4	46.3	46.5
PIAT-Reading Comprehension	45.0	45.2	45.1	45.0	44.8
PIAT-Reading Recognition	49.8	49.5	50.1	49.9	49.1
Ages 11-12					
PIAT-Math	54.0	50.5***	54.4	53.6	54.0
PIAT-Reading Comprehension	52.1	50.5	52.5	52.2	50.7**
PIAT-Reading Recognition	59.1	55.7**	59.8	59.3	57.0***
Hispanic and Black Females					
Ages 5-6					
PIAT-Math	14.8	14.1	14.9	15.4	14.7
PIAT-Reading Comprehension	16.9	15.9**	17.2	17.3	16.8
PIAT-Reading Recognition	17.6	16.6*	17.8	18.1	17.4
Ages 7-8					
PIAT-Math	28.1	26.6	28.1	28.9	29.0
PIAT-Reading Comprehension	30.1	28.9	30.3	31.0	30.0
PIAT-Reading Recognition	32.5	30.8**	32.8	33.0	32.8
Ages 9-10					
PIAT-Math	41.1	38.9**	41.0	42.5**	41.5
PIAT-Reading Comprehension	39.9	38.1*	40.1	40.5	39.3
PIAT-Reading Recognition	44.4	43.1	44.7	44.7	44.5
Ages 11-12					
PIAT-Math	47.6	45.2*	47.6	48.2	47.7
PIAT-Reading Comprehension	46.2	44.1	46.3	46.4	46.2
PIAT-Reading Recognition	53.3	49.8*	53.1	54.1	53.6

The covariates used in my models are similar to those used by Kaestner and Grossman (2007) and Averett and Stifel (2007) in their analyses and include a multitude of child, family, and environmental factors. The logic behind the choice of covariates come from the literature on the production of educational achievement, which include child endowment and family, school, teacher, and peer inputs (e.g Todd & Wolphin, 2007). Common child demographic characteristics such as age in months, grade, region of residence, and whether the area of residence is urban or rural[8] are included in the models. As not all factors that influence child academic achievement are measured in the NLSY Child/YA, variables are used to proxy these missing inputs. Maternal characteristics are added as proxies to control for mother's unobserved abilities and attitudes that may affect child academic outcomes. They also proxy for quality and quantity of time spent by the mother with the child. Such variables include mother's AFQT score (quadratic), marital status, highest grade completed, whether there was a library card in her household at the age of 14, whether she lived with both her parents until the age of 18, the number of weeks and hours worked in the past year (quadratic), and an interaction term of weeks and hours worked in the past year. Early childhood environment is controlled for by using child birth weight and mother's age at birth. Other covariates included are number of children in the household and household income of the mother[9] (quadratic), which affect parents' investment (i.e. time and money) into each of their children. Year dummies are also added to the models and body weight enters the estimation either as a set of dummy variables for weight status (with the

[8] Here, region of residence and whether the area of residence is urban or rural is given by the mother's place of residence, as the NLSY Child/YA data does not provide this information specifically for children under young adult age. Although it may be possible that the child does not live full-time with the mother, the child needs to be living with the mother for at least part of the year to be interviewed for the NLSY. Hence, measures for the mother may be appropriate to use as proxies, given that specific data for the child is not available.

[9] Mother's household income is used because household income of the child is not available in the dataset. For the reason mentioned above (see footnote 8), I argue that this variable is appropriate to be used as a control in my models.

excluded group being those of a normal weight) or BMI z-score. BMI z-scores allow for estimations of the effects of more incremental changes in BMI for age. Black et al. (2015) suggests that the relationship between BMI and cognitive achievement is likely to be nonlinear and omits underweight children when BMI z-scores are used, allowing for increases in BMI to be interpreted as moving further away from a healthy weight. Here, I do the same for my OLS and FE models that use BMI z-scores.

V. Results

Table 3 and Table 4 show the results from the OLS and FE results for boys and girls by race, respectively. OLS results show that there is a positive relationship between being obese and reading comprehension test scores for Hispanic and black boys, and a negative relationship between being overweight on reading comprehension test scores for white boys. Under a fixed effects specification where unobserved heterogeneity is addressed, there remains a statistically significant negative effect of being overweight on reading scores for white boys. For girls, there is no statistically significant effect of being obese under and OLS specification. In the fixed effect model, however, I find that there is a negative effect of being obese on reading scores for Hispanic and black girls.

For the IV and Lewbel IV models, BMI z-scores are treated as endogenous. I do not conduct IV estimations with weight status categories as endogenous variables, as a single endogenous variable (BMI z-scores) is much easier to estimate than having numerous binary endogenous variables. In the traditional IV estimation, maternal BMI in 1985 and its square (which were also used by Averett and Stifel (2007) as instruments in their IV models) were used as instruments for BMI z-scores.

Table 3 – OLS and FE Results for Boys

	Male Children			
	PIAT-Math		PIAT-Reading Comprehension	
	OLS	FE	OLS	FE
Non-Hispanic, Non-Black				
Underweight	-1.07 (0.50)**	-0.64 (0.49)	-0.37 (0.54)	0.35 (0.56)
Overweight	-0.30 (0.34)	-0.22 (0.36)	-1.06 (0.37)***	-1.26 (0.41)***
Obese	-0.16 (0.34)	-0.13 (0.47)	0.46 (0.37)	-0.04 (0.54)
Number of Observations	4800	4800	4690	4690
R squared	0.79	0.89	0.73	0.85
BMI z-score	-0.15 (0.12)	-0.11 (0.18)	-0.06 (0.14)	-0.08 (0.21)
Number of Observations	4494	4494	4390	4390
R squared	0.79	0.89	0.73	0.85
Hispanic or Black				
Underweight	-0.05 (0.57)	-1.19 (0.60)**	0.22 (0.58)	-1.00 (0.61)
Overweight	0.71 (0.40)*	0.00 (0.46)	0.53 (0.41)	0.76 (0.47)
Obese	0.10 (0.39)	-0.10 (0.58)	0.83 (0.39)**	0.87 (0.58)
Number of Observations	3895	3895	3790	3790
R squared	0.73	1705	0.67	0.81
BMI z-score	-0.00 (0.14)	0.03 (0.26)	0.24 (0.14)*	0.39 (0.23)*
Number of Observations	3622	3622	3525	3525
R squared	0.72	0.85	0.67	0.8

* 0.05 < p-value < 0.10

**0.01 < p-value < 0.05

***p-value < 0.01

Models include dummy variables for grade, year, child age in months, birth order, mother's age at birth, mother's marital status, highest grade level completed by the mother, whether there was a library card in the household of the mother at age 14, whether she lived with both her parents until age 18, and child birthweight, mother's household income squared, mother's AFQT score squared, weeks and hours worked squared in past year, an interaction between weeks and hours worked in past year, mother's region, and whether the area of mother's residence is urban or rural

Table 4 – OLS and FE Results for Girls

	Female Children			
	PIAT-Math		PIAT-Reading Comprehension	
	OLS	FE	OLS	FE
Non-Hispanic, Non-Black				
Underweight	-1.22 (0.49)**	-0.01 (0.51)	0.20 (0.52)	-0.15 (0.55)
Overweight	-0.30 (0.30)	-0.66 (0.35)*	-0.20 (0.32)	-0.15 (0.38)
Obese	-0.04 (0.34)	-0.17 (0.51)	-0.25 (0.36)	-0.84 (0.55)
Number of Observations	4705	4705	4610	4610
R squared	0.8	0.89	0.75	0.86
BMI z-score	0.06 (0.12)	-0.03 (0.19)	-0.16 (0.12)	-0.02 (0.20)
Number of Observations	4440	4440	4349	4349
R squared	0.8	0.89	0.75	0.86
Hispanic or Black				
Underweight	-0.51 (0.51)	-0.34 (0.52)	-0.23 (0.53)	-0.11 (0.58)
Overweight	0.17 (0.32)	-0.02 (0.35)	0.00 (0.33)	-0.40 (0.39)
Obese	0.15 (0.31)	0.01 (0.44)	-0.56 (0.32)*	-1.10 (0.50)**
Number of Observations	4605	4605	4502	4502
R squared	0.75	0.87	0.69	0.81
BMI z-score	-0.01 (0.12)	0.05 (0.18)	-0.23 (0.12)*	-0.26 (0.20)
Number of Observations	4326	4326	4227	4227
R squared	0.75	0.87	0.69	0.8

* 0.05 < p-value < 0.10

**0.01 < p-value < 0.05

***p-value < 0.01

Models include dummy variables for grade, year, child age in months, birth order, mother's age at birth, mother's marital status, highest grade level completed by the mother, whether there was a library card in the household of the mother at age 14, whether she lived with both her parents until age 18, and child birthweight, mother's household income squared, mother's AFQT score squared, weeks and hours worked squared in past year, an interaction between weeks and hours worked in past year, mother's region, and whether the area of mother's residence is urban or rural

Results for IV estimation and the Lewbel IV estimation are presented in Table 5. Tests for endogeneity revealed that child weight, measured by BMI z-scores, is endogenous. Using mother's historical BMI and its square as instruments, I find a statistically significant negative effect of BMI z-scores on test scores for all race/gender groups. However, using Lewbel's generated instruments, I find no effect of BMI on test scores. Although these results may shed some light on the effect of body weight on child academic achievement, I approach these estimates with caution. Table 6 shows postestimation statistics for the traditional IV and Lewbel IV models. Although postestimation tests suggest that the traditional instruments are valid and strong, as discussed in Section III, there is the possibility that these variables (historical maternal BMI and its square) do not meet the exclusion restriction required of a valid instrument. The

Table 5 – IV and Lewbel IV Results

	PIAT-Math		PIAT-Reading Comprehension	
	IV	Lewbel IV	IV	Lewbel IV
Male Children				
Non-Hispanic, Non-Black				
BMI z-score	-2.57 (0.60)***	0.06 (0.10)	-2.20 (0.63)***	0.03 (0.11)
Number of Observations	4444	4800	4343	4690
R squared	0.76	0.78	0.7	0.72
Hispanic or Black				
BMI z-score	-3.68 (0.62)***	0.00 (0.11)	-2.71 (0.62)***	0.14 (0.11)
Number of Observations	3565	3895	3467	3790
R squared	0.64	0.71	0.6	0.65
Female Children				
Non-Hispanic, Non-Black				
BMI z-score	-0.96 (0.43)**	0.18 (0.10)*	-1.72 (0.47)***	-0.19 (0.10)*
Number of Observations	4362	4705	4273	4610
R squared	0.78	0.79	0.73	0.74
Hispanic or Black				
BMI z-score	-1.65 (0.51)***	0.10 (0.09)	-1.19 (0.52)**	-0.12 (0.10)
Number of Observations	4230	4605	4136	4502
R squared	0.73	0.74	0.67	0.68

* 0.05 < p-value < 0.10

**0.01 < p-value < 0.05

***p-value < 0.01

Table 6 – Test Statistics for IV and Lewbel IV Models

	Traditional IV		Lewbel IV	
	Math	Comp	Math	Comp
Non-Hispanic, Non-Black Males				
Underidentification test p-value	0.000	0.000	-	-
Cragg-Donald F statistic	107.198	106.867	-	-
Sargan statistic p-value	0.072	0.158	0.001	0.000
Breusch-Pagan test of heteroskedasticity	-	-	0.000	0.000
Hispanic or Black Males				
Underidentification test p-value	0.000	0.000	-	-
Cragg-Donald statistic	110.714	106.276	-	-
Sargan statistic p-value	0.934	0.682	0.099	0.077
Breusch-Pagan test of heteroskedasticity	-	-	0.000	0.000

	Traditional IV		Lewbel IV	
	Math	Comp	Math	Comp
Non-Hispanic, Non-Black Females				
Underidentification test p-value	0.00	0.00	-	-
Cragg-Donald F statistic	167.3	162.6	-	-
Sargan statistic p-value	0.94	0.07	0.046	0.001
Breusch-Pagan test of heteroskedasticity	-	-	0.000	0.000
Hispanic or Black Females				
Underidentification test p-value	0.00	0.00	-	-
Cragg-Donald statistic	119.8	117.6	-	-
Sargan statistic p-value	0.51	0.37	0.325	0.127
Breusch-Pagan test of heteroskedasticity	-	-	0.000	0.000

IV and Lewbel models include dummy variables for grade, year, birth order, mother's marital status, highest grade level completed by the mother, whether there was a library card in the household of the mother at age 14, whether she lived with both her parents until age 18, and child age in months, mother's age at birth, child birthweight, mother's household income squared, mother's AFQT score squared, weeks and hours worked squared in past year, an interaction between weeks and hours worked in past year, mother's region, and whether the area of mother's residence is urban or rural

Lewbel IV can be used when traditional instruments may not be available or weak. One thing to note here is that Lewbel estimates may be sensitive to the choice of Z. There are no accepted approaches for the optimal selection of Z. Thus, I use the standard approach of presenting results based on Z= all of X (i.e. all exogenous variables in the model). The condition of heterogeneity in the first stage regression is met, as shown in the Breusch-Page test results. However, the

Sargan overidentification test p-statistics are extremely low, which raises doubts about the validity of the generated instruments.

VI. Discussion

In studying the causal effect of obesity on academic achievement, my preferred estimates are those of the fixed effects model. The fixed effects model addresses the problem of unobserved heterogeneity, and thus controls for unobserved time-invariant child and family characteristics that may also affect academic achievement. However, it is important to remember that the fixed effects model does not address the issue of reverse causality and simultaneity. Although instrumental variable estimations are presented in this paper, I warn that these results must be approached with caution. There is a possibility that the usage of past maternal BMI and its square as instruments is not appropriate, given that they may be correlated with a whole host of environmental factors that affect both weight status of the child and his or her academic achievement. As for the Lewbel IV estimation, despite the presence of heteroscedasticity in the first stage bodyweight equation, generated instruments may not be valid, as shown in the rejection of the null hypothesis of the overidentification test.

To summarize, under a fixed effects specification, there is a negative effect of being overweight on reading test scores for white boys and a negative effect of being obese on reading test scores for Hispanic and black girls. These results are consistent with other literature on the topic finding a negative relationship between obesity and academic achievement. This result is also consistent with Averett and Stifel's (2010) findings of negative effects of being overweight on reading scores for white boys and black girls. (They do, however, find negative effects of being overweight on test scores for other gender/race groups while I do not). An interesting point here is that the effect of obesity on academic achievement on black and Hispanic boys are positive, though not at conventional levels.[10] The fact that the signs on the estimated coefficients of being obese are the opposite for white boys and black/Hispanic boys show the importance of stratifying data by race when analyzing the effect of body weight on academic achievement. Reasons my results may differ from Kaestner and Grossman (2009), who find no effect of obesity on child academic achievement despite the fact that the same dataset was used, may be in part, because they did not stratify their sample by race and gender. Previous literature, and I, in this paper, have found that the effects of obesity differ not merely by gender, but by race. Aggregating the data may drown out effects for certain subgroups.

In this paper, I find that demographic differences, particularly that of race and gender, are important to consider in analyzing the effects of obesity on child educational outcomes. One point to note here is that I did not stratify my sample by age. For example, the effects of obesity at the ages of 5 and 6 may be different from those at ages 11 and 12. Since children go through many developmental changes, particularly in early childhood, the effects of obesity may differ as children grow older.[11] In future work, it would be interesting to stratify populations, not only by race and gender, but by age, to see whether there is a point at which weight status starts having a greater effect on educational outcomes, in order to determine the best age(s) at which intervention programs may be most effective.

[10] Cawley (2004) finds a similar result when he studies the effects of weight on adult wages. He finds that heavier black males tend to earn more and that weight is positively correlated with education and intelligence test scores. Although Cawley's work focuses on adults, it may be possible that this positive effect of overweight and obesity starts at a younger age for black males. Ding et al. (2009) also find a positive effect of obesity on academic achievement for high school boys under a 2SLS specification, though not statistically significant at conventional levels.

[11] Kaestner and Grossman (2009) conclude that there are age-specific effects of obesity

References

Averett, S., & Stifel, D. (2007). Food for thought: The cognitive effects of childhood malnutrition in the United States. *Mimeo*.

Averett, S. L., & Stifel, D. C. (2010). Race and gender differences in the cognitive effects of childhood overweight. *Applied Economics Letters,17*(17), 1673-1679. doi:10.1080/13504850903251256

Black, N., Johnston, D. W., & Peeters, A. (2015). Childhood obesity and cognitive achievement. *Health Economics,24*(9), 1082-1100. doi:10.1002/hec.3211

Burkhauser, R. V., & Cawley, J. (2008). Beyond BMI: The value of more accurate measures of fatness and obesity in social science research. *Journal of Health Economics,27*(2), 519-529.

Cawley, J., & Burkhauser, R. V. (2006). Beyond BMI: The value of more accurate measures of fatness and obesity in social science research. *NBER Working Paper Series,* (12291).

Cawley, J. (2004). The impact of obesity on wages. *The Journal of Human Resources,39*(2), 451-474. doi:10.2307/3559022

Cho, S., Lambert, D. M., Kim, H. J., & Kim, S. G. (2009). Overweight Korean adolescents and academic achievement. *Journal of Family and Economic Issues,30*(2), 126-136. doi:10.1007/s10834-009-9147-x

Crosnoe, R., & Muller, C. (2004). Body mass index, academic achievement, and school context: Examining the educational experiences of adolescents at risk of obesity. *Journal of Health and Social Behavior,45*(4), 393-407.

Datar, A., & Sturm, R. (2006). Childhood overweight and elementary school outcomes. *International Journal of Obesity,30*(9), 1449-1460.

Davis, C. L., & Cooper, S. (2011). Fitness, fatness, cognition, behavior, and academic achievement among overweight children: Do cross-sectional associations correspond to exercise trial outcomes? *Preventive Medicine,52*, S65-S69. doi:10.1016/j.ypmed.2011.01.020

Ding, W., Lehrer, S. F., Rosenquist, J., & Audrain-Mcgovern, J. (2009). The impact of poor health on academic performance: New evidence using genetic markers. *Journal of Health Economics,28*(3), 578-597. doi:10.1016/j.jhealeco.2008.11.00

Eide, E. R., Showalter, M. H., & Goldhaber, D. D. (2010). The relation between children's health and academic achievement. *Children and Youth Services Review,32*(2), 231-238. doi:10.1016/j.childyouth.2009.08.019

Fletcher, J., & Lehrer, S. (2009). Using genetic lotteries within families to examine the causal impact of poor health on academic achievement. *NBER Working Paper Series,* (15148). doi:10.3386/w15148

Geier, A. B., Foster, G. D., Womble, L. G., McLaughlin, J., Borradaile, K.E., Nachmani, J., Sherman, S., Kumanyika, S., & Shults, J. (2007). The relationship between relative weight and school attendance among elementary schoolchildren. *Obesity Research*, *15*, 2157–2161.

Gunstad J, Paul RH, Cohen RA, Tate DF, Spitznagel MB, Grieve S, Gordon E. 2008. Relationship between body massindex and brain volume in healthy adults. *International Journal of* Neuroscience 118(11): 1582–1593.

Heckman, J. J. (2006). Skill formation and the economics of investing in disadvantaged children. *Science,312*(5782), 1900-1902. doi:10.1126/science.1128898

Kaestner, R., & Grossman, M. (2009). Effects of weight on children's educational achievement. *Economics of Education Review,28*(6), 651-661. doi:10.1016/j.econedurev.2009.03.002

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics,30*(1), 67-80. doi:10.1080/07350015.2012.643126

Lindeboom M, Lundborg P, van der Klaauw B. 2010. Assessing the impact of obesity on labor market outcomes. E*conomics & Human* Biology 8(3): 309–319.

Puhl RM, Latner JD. 2007. Stigma, obesity, and the health of the nation's children. *Psychological Bulletin* 133(4): 557.

Redline, S., Tishler, P. V., Schluchter, M., Aylor, J., Clark, K., & Graham, G. (1999). Risk factors for sleep-disordered breathing in children: Association with obesity, race and respiratory problems. *American Journal of Respiratory and Critical Care Medicine*, *159*(5), 1527–1532.

Sabia, J. J. (2007). The effect of body weight on adolescent academic performance. *Southern Economic Journal,73*(4), 871-900.

Sabia, J. J., & Rees, D. I. (2015). Body weight, mental health capital, and academic achievement. *Review of Economics of the Household,13*, 653-684.

Scholder, S. H., Propper, C., Windmeijer, F., Smith, G. D., & Lawlor, D. A. (2009). The effect of child weight on academic performance: Evidence using genetic markers. Retrieved from http://www.bris.ac.uk/ifssoca/outputs/conferences/kesslerpaper.pdf

Taki Y, Kinomura S, Sato K, Inoue K, Goto R, Okada K, Uchida S, Kawashima R, Fukuda H. 2008. Relationship between body mass index and gray matter volume in 1,428 healthy individuals. *Obesity* 16(1): 119–124.

Todd, P. E., &Wolpin, K. I. (2007). The production of cognitive achievement in children: Home, school, and racial test score gaps. *Journal of Human Capital*, *1*, 91–136.

Weden, M. M., Brownell, P. B., Rendall, M. S., Lau, C., Fernandes, M., & Nazarov, Z. (2013). Parent-reported height and weight as sources of bias in survey estimates of childhood obesity. *American Journal of Epidemiology,178*(3), 461-473. doi:10.1093/aje/kws477

Zavodny, M. (2013). Does weight affect children's test scores and teacher assessments differently? *Economics of Education Review,34*, 135-145. doi:10.1016/j.econedurev.2013.02.003