Childhood obesity effect on human capital accumulation

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Major Paper presented to the
Department of Economics of the University of Ottawa
in partial fulfillment of the requirements of the M.A. Degree
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Ottawa, Ontario
September 2016

Acknowledgement

I would like to express my sincere gratitude to my supervisor Prof. Victoria Barham for the help and useful advice. Her guidance helped me a lot in writing the major paper.

Besides my supervisor, I also want to thank Vivian Ellis, Olga Milliken, Yang Mao and Rebekah Owusu for their encouragement, insightful comments and useful advice.

1. Introduction

In recent years, a number of researchers have investigated the link between cognitive ability in children and economic outcomes in adulthood. As demonstrated by Currie (2000), the measured cognitive and verbal abilities of children help predict human capital in adulthood and therefore earnings and employment. Measured cognitive ability of children is also a powerful determinant of the likelihood that a child will complete high school, as well as the likelihood that they commission a crime or partake in other risky activities (Cunha and Heckman 2007). But what determines cognitive ability? Although genetics are undoubtedly a factor, there is considerable evidence that cognitive ability is influenced by childhood health; after controlling for socio-demographic variables, adverse health during childhood is associated with both lower measures of cognitive outcomes and schooling attainment (Kaestner & Corman 1995, Currie & Stabile 2006, Datar & Sturm 2006, Salm 2008, Currie 2006, Cawley 2008, Sabia 2007, Ding 2008, Paxson & Schady 2007).

One of the potential pathways by which health factors may influence cognitive outcome is obesity. There is increasing awareness that childhood obesity is correlated with adverse physical, social and intellectual developmental outcomes in children in both the short and long term. Higher levels of ghrelin (a peptide hormone produced by ghrelinergic cells in the gastrointestinal tract) have been linked to higher brain functioning, and low levels of the hormone have been linked to obesity (Diano & Farr 2006). Obese children are at greater risk of health problems, including sleep apnea, hypertension, diabetes and orthopaedic complications (Must & Strauss 1999). Obese children may suffer from discrimination from same-age students, and day care providers and teachers (John et al. 2008, Mahoney, Lord, & Carryl 2005). Being subject to such stigma makes it more difficult for obese children to learn effective social skills and to develop satisfying peer relationship (Datar & Sturm, 2006; Gable, Krull & Chang 2009). Moreover, obese children are more likely to struggle with overweight or obesity as adults (Singh et al 2008). In developed countries, obesity in adults is associated with worse labor market outcomes and lower wages (Cawley, 2004). Such findings are particularly troubling given that childhood obesity is becoming more widespread.

In Canada, the prevalence of obesity and overweight in the school-aged population (2 to 17 years of age) almost doubled between 1978-1989 and 2005, increasing from 15 to 26 percent[1]. This phenomenon is very serious and needs more attention since poor health may adversely affect child cognitive ability or academic achievement and then affect human capital development.

The outline of this paper is as follows. Below, I present a selective review of the literature examining the link between obesity and adverse health outcomes, as well as a more comprehensive survey of the papers which have studied the relationship between obesity and cognitive outcomes. From this review of the literature, it emerges that there have been no studies of the link between obesity and cognitive outcome conducted using Canadian data. Also, most of the existing papers which find a link between obesity and cognitive outcomes do not deal properly with the problem of causality. That is, these studies do not study whether it is children with lower cognitive ability who become obese, or whether it is obesity which causes poor cognitive development. The objective of this study is to address these gaps in the literature. Section four explains the empirical methodology and section three describes the data used for this analysis. Section five reports the results and section six concludes.

2. Literature review

There is a very large literature which has documented the link between obesity in children and adverse health outcomes. Severely obese young children are more likely to subsequently suffer from serious health problems such as gallstones, hepatitis, sleep apnea and increased intracranial pressure (Must & Strauss, 1999). Obesity during adolescence is associated with insulin resistance and hyperandrogenemia, especially in girls, and menstrual abnormalities are common (Richards et al, 1985). Overweight children mature earlier than their peers (Garn, Clark et al 1975) and this in turn increases the likelihood of overweight and obesity in adulthood (Lenthe et al, 1996). Several studies have found that obese children and adolescents, compared to those who are not obese and are healthy, will have worse health-related qualify of life (Schiwimmer, Burwinkle & Varni, 2003; Varni, Seid & Kurtin, 2001). Childhood obesity also adversely affects measures

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1.Curbing Childhood Obesity: A Federal, Provincial and Territorial Framework for Action to Promote Healthy Weights, Public Health Agency of Canada, p.1. http://www.phac-aspc.gc.ca/hp-ps/hl-mvs/framework-cadre/index-eng.php of children's mental health and psychosocial outcomes, such as low self-esteem and depression (French, Story & Perry, 1995; Wallace, Sheslow & Hassink, 1993).

In this literature review, however, we are principally concerned with the link between childhood obesity and measures of cognitive ability. Although this is not a large literature, it turns out to be useful to group papers together by considering the age of the subjects. Three papers have looked at obesity in adolescence. Sabia (2006) uses data on adolescents (students enrolled in grades seven through twelve) from the National Longitudinal Study of Adolescent Health in the United States. Sabia uses a combination of GPA (grade point average) and math and English language test scores as dependent variable and uses BMI (body mass index) to represent the weight status: Overweight, underweight and normal weight. Ordinary least squares, instrumental variables and fixed effects models are used to explore the association between adolescent body weight and academic performance. The results reveals that for adolescents (14-17 years old), there exists a negative relationship between body weight and academic performance for white females. However, there is no significant association between these variables for non-white female and males. They conclude that implementing obesity-reduction policy does not matter greatly for human capital formation.

Sigfusdottir, Kristjansson and Allegrant (2007) use a nationally representative cross-sectional data sample of 14 and 15 years old schoolchildren from Iceland. Their dependent variable is the students' self-reported average scores in the core subjects of Icelandic, Mathematics, English and Danish (alternatively Swedish or Norwegian). They use ordinary least squares to explore the differences between those students above the 85 percentile for BMI-- that is, students who are overweight or obese, and normal weight students. They find that students with higher BMI will have bad self-esteem, poorer grades and are more likely to be depressed than those with a lower BMI. They also find that higher BMI is related to lower parents of education, less reported physical activity and less nutritious food. They find that the body mass index (BMI) is significantly and negatively correlated with grades in language classes and mathematics. They also find that BMI has much more impact than any of the other variables (including physical activity) on academic achievement. They conclude that among the health related indicators, BMI is the most strongly correlated with academic outcomes, and that diet and physical activity have less effect on academic outcomes. They also observe that nutritionally poor dietary choices and lack of physical activity are risk factors for obesity.

Booth, Tomporowski, Boyle, Ness, Joinson, Leary and Reilly (2014) use a sample of 11, 13 and 16 year old children from the Avon Longitudinal Study of Parents and Children. Unlike the Iceland study, they use grades obtained on the General Certificate of Secondary Education (GCSE) exam as the dependent variables. They use a categorical variable to represent the obesity status: healthy weight, overweight and obese. This paper also uses ordinary least squares to estimate the effect and finds that obesity reduces GSCE scores. The authors also use depressive symptoms, IQ and age of menarche as controls, and finds that these variables do not have an effect. They conclude that adolescent obesity really does have an adverse impact on future academic outcomes, particularly for girls.

Note that these three papers found the same conclusion that for female adolescents, the body mass index (or overweight) has a negative effect on their academic performances. It is suggested that this may be due to discrimination against overweight white females from teachers, which in turn affects academic achievement. But these studies have significant limitations: they do not fully control for factors such as self-esteem or the school or family environment which may impact both obesity and cognitive outcomes. In particular, this means they are not dealing with properly with endogeneity.

Turning to school-aged children, Kaestner and Grossman (2009) use both longitudinal and cross-sectional features of American NLSCY data on children from ages 5 to 12 to compare the achievement test scores of overweight and obese children versus scores of normal weight children. They find that children who are overweight or obese have achievement scores that are about the same as children who are of average weight. They use first-difference estimates, as well as fixed effects and instrumental variables models, and find that the absence of a relationship between weight and academic achievement is robust to different empirical strategies.

Carter, Dubois and Ramsey (2010) use the confidential data set for cycles 1 and 5 of the Canadian National Longitudinal Study of Youth and Children. They observe children are 2-5 years old in cycle 1 and observe the same children six year later (cycle 6). They use the Canadian standardized IRT math score to measure academic achievement and also use the PPVT-R (Revised Peabody Picture Vocabulary Test), which is administered when children were 4-5 years old as a baseline predictor of academic aptitude. An innovative feature of this paper is that they track the change in obesity status by creating a categorical variable, obesity status which takes on the values never obese, grow out of obese, developing obese, always obese. They run the ordinary least squares model and find that there is no difference in math achievement between children who became obese as compared to those who were never obese. However, they find that those who grow out of obese obtain much higher scores than those who were never obese. They conclude that the relationship between obesity status and math scores is not clear and needs more investigation. A weakness of their approach, however, is that they do not control appropriately for unobserved heterogeneity between children who are never obese versus those who grow out of obesity.

Palermo and Dowd (2012) use the longitudinal data from the Child Development Supplement (CDS), an American data set--the Panel Study of Income Dynamics. The observations are of children from ages 5 to 19 from three different waves. They initially use the OLS regression model on panel data from all three waves to estimate the relationship between BMI and cognitive outcomes. They use several measures of cognitive abilities and non-cognitive abilities, including the Woodcock Johnson Revised Tests of Achievement. Since unobserved heterogeneity may lead to the correlation of independent variables and error term in the OLS model, they re-estimate the within-child fixed effects model. The authors argue that this model controls for the individual-family and community-level fixed effects since the communities and family in which the child lives does not change substantively during the time frame of the study. They also run a sibling fixed effects model to control for family background and identify effects of weight status differences between siblings. Using OLS, they find that obese girls have higher scores than normal weight in cognitive outcome. But for non-cognitive outcome, they find that obese girls have much lower positive behaviors scores compared to normal weight girls. In contrast, when looking at cognitive outcomes for boys, the association is negative but small; for non-cognitive outcomes, there is no effect. The authors conclude that childhood obesity is negatively associated with behavioral but not cognitive outcomes in females, and the cognitive and behavioral outcomes are affected by race and ethnicity.

Afzal and Gortmaker (2014) use data from two nationally representative cohorts of children in the 1979 American National Longitudinal Survey of Youth and observe children who are 2-8 years old in 1988 and again 6 years later (1994). Like Carter (2010), they define the obesity status as never obese, always obese, become obese, become non-obese. They use four cognitive tests as dependent variables: the PPVT-R, WISC-R and PIAT math and reading comprehension test scores. They use ordinary least squares to estimate the effect of obesity on cognitive test outcomes and that those who are always obese get much lower cognitive test scores than those who are never obese. But when they re-estimate using the fixed-effects model, they find that the association is not significant. They conclude that there is not a strong longitudinal relationship between obesity and cognitive test scores.

Black et al (2015) use waves 1-5 data of a representative panel survey-- The Longitudinal Study of Australian Children and observes children who are 4-5 years old in wave 1 and observe them again from waves 3 to wave 5. The authors use nationally- administered test scores in math and literacy to measure cognitive ability. They use simple linear regression to estimate the effect of weight on cognitive achievement and finding that there exists a negative association between these two. They also use a within-child fixed effects model to explore the variation in cognitive achievement and obesity for the same child across time. They then extend the original model to allow lagged cognitive achievement to influence current cognitive achievement and find that there exists a strong positive association between cognitive achievement and its lagged values. But overall they obtain similar results with respect to the link between weight and cognitive outcome as with the OLS estimates. Finally they use instrumental variables (IV) estimators to address endogeneity. They choose the obesity status of mothers and fathers when children is aged 4/5 as instruments and find that the estimates are much more negative than the OLS coefficients. They ultimately conclude that academic achievement of girls is not affected by obesity status, after controlling for socio-demographic variables, but there is a negative association for boys that does not disappear after account is for socio-demographic factors.

Overall, there is no clear consensus about the relationship between childhood obesity and cognitive outcome in school aged children; the relationship is complex and still need to be further investigated. Many authors find different results for boys and girls, but there is no satisfactory explanation as to why gender differences might be expected. A number of limitations can also be identified, in particular, the detrimental effects of obesity may take several years to impact the cognitive and school performances; and more address potentially reverse causation, which will lead to the possibility that lower cognitive score will impact the obesity status of children to some extent. Moreover, the fixed-effects model should include the time-varying characteristics.

Finally, there are four papers which focuses on young children or children in kindergarten. Datar, Strum and Magnabosco (2004) use data from American Early Childhood Longitudinal Study-Kindergarten Class (ECLS-K).Their subject are initially observed in the fall of their kindergarten (1998, wave1) and then in spring session of kindergarten (wave 2), in the fall of grade 1 (wave 3) and spring of grade 1 (wave 4).They use the math and reading item response scale (IRT) scores as dependent variables. They run the cross-section regression model and find that overweight children usually have lower math and reading tests scores than their non-overweight peers when they are in kindergarten. They also run the longitudinal regression model to estimate the baseline weight status effect on the academic outcome when they are in grade one and also includes the kindergarten scores as independent variables. They find that the relationship between overweight status and academic performance in grade one is insignificant.

Datar and Sturm (2006) use the same data set but observe the subjects for a longer period in kindergarten, grade 1, grade 3 and grade 5. They also include other dependent variables: teacher-reported behavior problems and teacher-reported social skills and approaches, grade repetition. They use the change in weight status as the independent variable: never overweight, become overweight, and always overweight. They use the ordinary least squares model to estimate the relationship between change in overweight status and school outcomes and find that reading and math scores are significantly higher for the never overweight children than for the overweight and become overweight children. They also find that always overweight children have more behavior problems and are more likely to repeat a grade. Also, the change in weight status—from not-overweight to overweight between kindergarten entry and end of third grade is strongly and positively correlated with third grade outcomes, for girls, but not for boys. Nonetheless, although the overweight has a highly statistically significant impact on cognitive outcomes, the actual effect is quite small as compared to the impact of family characteristics.

Cawley and Spiess (2008) also explore the relationship between obesity and skill attainment in early childhood. They use data from the German Socio-Economic Panel Study. They use ordinary least squares and ordered probit models to examine whether results are driven by differences between the immigrant and native-born population. They conclude that childhood obesity is associated with lower skill attainment at ages 2–3 years—younger than previously appreciated. They also find that the relationship between obesity and skill attainment is much stronger among boys than girls. They argue that there is bi-directional causality: obesity causes developmental delays, and slow development also cause obesity. This is because boys who are obese lose the opportunity of developing their social skills. However, having fewer playmates also increases the risk of becoming obese. They also find that bad physical health conditions and the mother's parenting style affect both weight status and skill development in children.

Yiting et al (2012) studies the relationship between these different indicators of cognitive functioning and child weight status, using date from the American Early Childhood longitudinal Study-K. Yang not only uses math scores, but also use teacher ratings of children's interpersonal skills and internalizing behaviors as dependent variables. Yiting finds that for boys and girls, both persistent and later onset group obese children perform less well in the math assessment compared to other children, but the obesity effect on academic performance lagged after kindergarten entry. And for the later onset groups, the weight effect only happens for girls. Notably, by fifth grade, their math grade is no longer significant linked to weight status.

While there is still not a clear picture, these papers seem to find some evidence that children who are obese in early childhood are likely to suffer adverse impact with respect to academic performance or skill attainment. There are also some limitations, in particular, some of outcome variables are teacher-reported, and may be biased because they may depend on the quality and psychological state of the teacher (Datar and Sturm, 2006).Other variables, like BMI, are reported by parents, and also potentially biased. And studies on school-aged children, endogeneity is not adequately addressed: obesity may cause developmental or bad academic outcome, but bad developmental outcomes also have a detrimental effect on obesity status. Also, the ordinary least squares models did only consider that there may be unobserved factors which may vary among children but are invariant across time. This may lead bias in the regression model.

There are three other studies which examine the relationship between children's health and indicators of human capital accumulation that are also worthy of mention. Currie and Stabile (2006) use Canadian and American data on children from 4 to 11 years old to assess whether children exhibits symptoms of Attention Deficit Hyperactivity Disorder (ADHD) do less well at school. They include grade repetition, math and reading scores and special education scores to represent human capital accumulation in childhood and sibling fixed effects model and family fixed effects model to control for unobserved heterogeneity. They also interact income and ADHD to investigate the mediated effect of income on ADHD. In both countries, they find that children with higher hyperactivity scores have outcomes that are worse in all dimensions, but the impact is lessened when the mother has more education. Also they find that hyperactivity is much more important than physical health conditions in determining children's achievement test scores and schooling attainment.

Ding, Lehrer, Rosenquist and Audrain-McGovern (2008) use an instrumental variables approach to study the impact of poor health on academic outcomes in adolescence. Their data primarily comes from the Georgetown Adolescent Research (GATOR) study which is a longitudinal study of adolescents in United States. They use a totally different empirical method three-stage least squares and use instrumental variables to estimate the equations to generate consistent estimates of the causal impact of health on education. They find that the impact of poor health on academic achievement is large, particularly for depression. Female adolescents are strongly affected by negative physical and mental health conditions, whereas males are not significantly impacted.

Salma and Schunk (2008) use administrative data from the German health service department and use the ordinary least squares and fixed effects sibling models to analyse the impact of health conditions on academic achievement. They examine how much of the child achievement gaps are attributed to the differences in health conditions. They find that the child health conditions negatively affect child development and the differences between childhood health conditions contributes to developmental gaps between socioeconomic groups.

These three papers all use longitudinal data and find evidence that childhood health conditions have a substantially negative effect on child development (academic achievement). These authors all use fixed effects model and instrumental variables to address endogeneity caused by unobserved heterogeneity.

Table 1, in the appendix, indicates the name and definitions of all of the dependent and independent variables. Table 2, also in the appendix, represents the sample mean and standard deviations for each of these variables.

3. Data and summary

I use confidential data set files from waves five to eight of the National Longitudinal Survey of Children and Youth of Canada. The NLSCY is a national, representative sample of Canadian children, and the survey was jointly conducted by Human Resources and Skills Development Canada (HRSDC) and Statistics Canada. The NLSCY began in 1994 and collects information on a great variety of factors which are believed to have an impact effect on children's health and development. The data on the subjects from newborns to age 16, is collected via an interview with the person most knowledgeable in the family (PMK), typically the mother; 16 - 25 year old subjects are interviewed directly. The target population comprises the non-institutionalized civilian population (aged 0 to 11 at the time of their selection) in Canada's ten provinces. It administers several different cognitive tests to preschool-aged children (not all waves use the same test); it also administers a mathematics test to second grade school-aged children, as well as problem-solving and literacy assessments to adolescents.

For the purposes of this study, I need to observe children over time. I use the samples of children who are at 0-1 years old in cycle 4, which also called cohort 4; I begin to observe them in cycle 5, when they are 2-3 years old, and continue to observe these children in cycle 6 (4-5), and cycle 7 (6-7). I also include cohort 5, who are first included in cycle 5. I begin to observe them in cycle 6

(2-3), and again in cycle 7 (4-5) and cycle 8 (6-7).The response rates were: for cohort 4, in cycle 5 87.01%; in cycle 6 65.5%, in cycle 7 62.2%. For cohort 5, the response rate in cycle 6 is 67.9%, in cycle 7 65.9%, in cycle 8 63.8%.

In this study, the sample is restricted to respondent for whom there are no missing observations for either BMI or for the outcome variables of interest. The final sample size is 3107 for individuals of cohort 4 and cohort 5 at age 2-3, 2942 for cohort 4 and 5 at age 4-5, 2842 for cohort 4 and 5 at age 6-7. Missing information for control variables were coded using dummy variables. Also, we exclude the observations which output variables value and BMI values are missing.

3.1 Outcome variables

I use a number of different outcome variables measures, some of which are better viewed as measures of academic achievement while others are closer to a measure of cognitive development. One weakness of the NLSCY is that few potential outcomes measures are collected for all cycles. For children who are at 2-3 years old, I use the Ages and Stages scores. The Ages and Stages component was generated for all children 3 to 47 months. The questions were grouped into the four categories listed below with each respondent receiving a score in the range of 0 to 60. For this has 4 variables which measure different part of child's development: (1) Communication: babbling; (2) Fine motor: hand and finger movement; (3) Problem solving: learning and playing with toys; (4) Personal and social solitary: social play and play with toys. A higher score is associated with higher development and so if obesity has an adverse impact on development at age 2-3, then the coefficient of the obesity variable should be negative.

Another outcome variable for young children is the motor and social development score, which measures the motor, social and cognitive development of children from birth to age 3. The questions vary by the age of the child, and the score ranges from 0-15. This outcome variable is available in all cycles. A higher score is associated with good motor, social and cognitive development ability and so if obesity has an adverse impact on development at age 2-3, then the coefficient of the obesity variable should be negative.

For the children who are at 4-5 years old, I use the Peabody Picture Vocabulary Test-Revised (ppvt-r), whoami scores, and number knowledge scores. These tests were administered to all 4-5 year old in both cycle 5 and cycle 6. PPVT-R scores measures receptive vocabulary of children. It was administered by the interviewer and generates a standardized score. A total raw score was calculated for each child who completed the PPVT–R based on the number of correct responses. Standardized scores allow for comparisons of scores across age groups. Obviously, a 5-year-old would be expected to perform better on the PPVT–R than a 4-year-old and have a higher raw score. The standardized score, however, takes into account the child's age. The score ranges from 41 to 165 and a high score indicates a highly developed vocabulary. If obesity adversely affects cognitive development, then the coefficient should be negative when PPVT-R is the outcome variable.

“Who am I” scores are also used as one of my outcome variables. The “Who am I” assessment was administered to children aged 4 or 5 year and to measure children’s understanding and use of conventional symbols and relevant early learning skills. For the NLSCY, the “Who am I” assessment is hand-scored by trained individuals at Statistics Canada and composed of three scales: a copying scale, a symbol scale and a drawing scale. It ranges from 10 to 40 and gives a general overview of the child’s developmental level. Higher scores means higher developmental levels. If obesity adversely affects academic achievement, then the coefficient should be negative when “Who am I” scores is the outcome variable.

The Number Knowledge Assessment is used as a dependent variable. The purpose of the Number Knowledge assessment is to assess the development of children’s understanding of numbers by examining their comprehension of the whole numbers, their ability to count, to understand when numbers are bigger or smaller, and basic arithmetic. For the NLSCY, the assessment is administered to 4- and 5-year-old children in cycle 5 to cycle 8. The age-equivalent score is derived based on the child’s responses to the items. The Age equivalent score assigns a point for each of the three levels passed. A child failing to answer any questions at the first level will get the minimum (0), whereas a child who answers all the questions of all three levels correctly receives the maximum (three). This overall scores range from 52 to 163, and higher scores represent a better understanding of the system of numbers. If obesity adversely affects academic achievement, then the coefficient should be negative when number knowledge is the outcome variable.

For the children who are at 6-7 years old, there are two test which are administered in cycle 7 and cycle 8--a math test a and a test of pro-social development scores. The mathematics tests is also a very important dependent variables. This variables measures the student's ability to do addition, subtraction, multiplication, and division operations on whole numbers, decimals, fractions, negatives and exponents. It consists of 20 computational questions answered in the home by respondents aged 7 to 15 in all cycles and is scored by the interviewer. The level of test (ranging from 2 to 10) is determined by the child's grade. Each child who took the Mathematics Test was given a raw score, and a scaled score. In this study, we only use the scaled score since they are units of a single scale with equidistant intervals that cover all of the grade levels. This scale scores range from 205-434 and higher scores indicate greater math ability. If obesity adversely affects academic achievement, then the coefficient should be negative when math scores is the outcome variable.

Pro-social scores was derived using the following items: How often do you say that this child is: Shows sympathy to someone who has made a mistake? They want the volunteers to choose answers from agree/not agree/strongly agree. This variables are responded by children's parent. This score range from 0-20 and higher scores indicate high pro-social behavior. If obesity adversely affects academic achievement, then the coefficient should be negative when math scores is the outcome variable.

To take the advantage of the longitudinal nature of our data set, it is desirable to observe the outcome variable of interest for the same child in multiple periods. Unfortunately, there is no actual measure of cognitive development which is collected in every cycle. The only possible outcome measure which is observed at ages 2-3, 4-5, and 6-7 is the hyperactivity/inattention score. This score is derived from the response provided by the PMK to the interviewer questions. This score is usually available in every cycles, and the score ranges from are 0-12 for 2-3 years old child, and 0-14 for which age above 4 years old. I find that as the age increase, the hyperactivity scores are becoming large this means that the symptoms of hyperactivity and inattention increase as children increase and I expect them to be positively correlated with the obese or overweight variables.

3.2 Independent variables

Our main interest is the link between obesity and cognitive development. As noted in the literature review, researchers typically use a categorical variable to capture obesity status, higher using normal/overweight/obese or the change in obesity status; that is always obese, become obese, formerly obese, never obese. One problem is that there are different definitions of obesity, including those developed by the World Health Organization, by the Center for Disease Control and Prevention, and by Cole (the latter is used by statistics Canada). In this study, I use two measures of obesity: a categorical variable which reflects obesity status in period t, as measured by the Center for Disease Control and Prevention, and a continuous variable BMI^2.I want to observe whether there is a relationship between obesity, cognitive development, and BMI^2 or not. BMI^2 is a continuous variable and has no upper band. Normal weight or healthy weight is 5^{th} percentile to less than the 85^{th} percentile; overweight is 85^{th} to less than the 95^{th} percentile and obese is equal to or greater than the 95^{th} percentile. We drop the underweight observations which is less than the 5^{th} percentile in BMI-for-age weight status categories and the corresponding percentiles. The reason why I did not include BMI into the regression model is I find from table 3 that BMI is highly correlated with the dummy variable: obese and overweight. I create the categorical variable and it has three values (0 for normal weight, 1 for overweight, and 2 for obese). I predicted that both of these variables should be negatively correlated with the outcome variable of interest. Here the overweight children takes up 13.3% at age 2-3, 15.04% at age 4-5, 17.64% at age 6-7. The obese children takes up 34.52% at age 2-3, 32.26% at age 4-5, and 25.71% at age 6-7. But, from table 3, we find that in the panel data set, the obese and BMI^2, BMI is highly correlated, so I only include the BMI^2 and the overweight as the independent variables. Notice that the advantage of BMI^2 is that it allows for a non-linear relationship between BMI and the outcome variable of interest.

In addition to our measure of obesity, we include a number of other socioeconomic and demographic characteristics of children and their parents as control variables. These variables capture information about important characteristics that are likely to have an independent impact on children's cognitive development.

The first variable is whether the child attends nursery or preschool; the answer is no/ yes/never and it is a categorical variable. Respondent who indicate never or no are coded as zero, respondent who indicated yes are coded as one. Children who attend nursery school should have been exposed to a good learning environment and may therefore score better on achievement test. They may also be more comfortable with testing. The expected coefficient is therefore positive. Children who have attend preschool or nursery takes up 22.9% at age 2-3 and 25.2% at age 4-5.

Another important variable is parent-reported health. The answer are excellent/very good/good/ fair/poor. Children whose parent reports that their health is poor or fair are coded as zero: children whose parent report that their health status is excellent, very good, good or fair are coded as one. Children whose parent-reported health status is good or excellent should do better on academic and cognitive tests, so the expected coefficient must be positive. Children who reported good health takes up to approximately 99% at each age range.

Family functioning scores are used to measure various aspects of family functioning, such as problem solving, communications. The scale is based on responses to twelve questions. This scale is used to measure various aspects of family functioning, e.g., problem-solving, communications, roles, effective involvement, effective responsiveness and behavior control. The score ranges from 0-15 and higher scores indicate family dysfunction. Since poor family functioning affect the child's mood and thus adversely affect the cognitive ability and test scores, the expected coefficient should be negative.

I also include parental depression scores which is calculated for the PMK from responses provided as act of the Parent Questionnaire. This score is available for age 0-5 years old in cycle 5 and 6, for age 0-9 years old in cycle 7 and cycle 8. This scale is aimed at gathering information about the mental health of respondents, with particular emphasis on symptoms of depression. The score is based on responses to statements such as "My sleep was restless." There are a number of studies which have demonstrated that the depression of the parent directly affects the development of the children.This depression score ranges from 0-36. High scores reflect the presence of depression symptom. So the coefficient for this variable should be negative.

We also include estimated total household income for every household. It is exact income and therefore actual variables which differs for every household. Since good household income can provide children a much better living environment and good study condition; I predict this coefficient is positive. From table 2, I find that Household estimated income is linearly increasing as child grow up and the depression score keeps decreasing as children is becoming elder. Since household income is a very large value, I expect the sign of coefficient to be positive and large value when estimating the obesity effect on all the cognitive and academic outcome variables except for the hyperactivity/inattention scores. The parents go to college or not is also an important role in affecting the cognitive outcome and I expect the sign to be positive. I also control for gender since many papers included in literature reviews has find that the obesity effect on cognitive outcomes differs by gender. In table 2, girls accounts for 48.23% at age 2-3, 49.35% at age 4-5, 49.39% at age 6-7.

4. Methodology

In this study, I am investigating the link between childhood obesity and cognitive outcomes. As my literature review has revealed, there is a lack of consensus over whether or not childhood obesity matters for cognitive outcomes, but one factor explaining the lack of consistency in the results may be the variety of empirical methods used to analyze this relationship. In my study, I use three different OLS models – a standard cross-sectional regression; the pooled regression model; and the fixed effects model. Below, I discuss each of these models.

4.1 Cross-sectional Regression Model

For the cross-sectional model, all of the respondents in the data set are observed at the same point in time, that is, the data set includes children who are ages 2-3 from cohort 5 along with children who are aged 4-5 from cohort 4. This means I pile up these two cohorts of the same age together: so I get the data of children which consist of cohort 4 and cohort 5 at age 2-3 and also observe them again at age 4-5, t then continue to observe them again at 6-7. I define 2-3 as period 1, 4-5 as period 2, 6-7 as period 3.

The basic relationship to be estimated can be expressed as

$$y_{it}^{j} = \alpha_{if} + \beta_1 overweight_{it} + \beta_2 BMI^2{}_{it} + \beta_3 x_{it} + \varepsilon_{it} \tag{1}$$

y_{it}^{j} is the cognitive ability measurement or academic achievement and it has a superscript j, i means the observation number and t means the time vector, here we only observe three periods , so t=1,2,3. Since there are so many different outcomes which measure the cognitive and academic achievement in different periods(t=1,2,3), so the number of j is different in every period, so when i=1, j=6,which means there are 6 different outcomes at age 2-3; when t=2, j=4, which means there are 4 different outcomes at age 4-5; when t=3, j=3, which means there are 3 different outcomes at age 6-7.

x_{it} is the vector of socioeconomic and demographic characteristics of individual i at time t, and ε_{it} means that the error term., α is the intercept. β_1 , β_2 and β_3 are vectors of estimation coefficient. A_s with all OLS regression procedures, the independent variables must be linearly independent of each other and uncorrelated with the error term for the estimates to be unbiased.

There is, however, reason to believe that there may be a serious problem of endogeneity when using this model. Endogeneity can arise for three reasons: omitted variables (model mis-specification); simultaneity (reverse causality); and measurement error. In this cross-sectional model, all the three potential sources of endogeneity may be a concern. For example, it may be that some genetic problem such as Down's Syndrome causes a child to be obese and to have poor cognitive outcomes, which means that there is endogeneity due to omitted variables. Also, several of the independent variables are based on the report of the PMK, who may be biased: the fact that 98% of PMK indicate that their child is in good or excellent health, although more than 2% of children are obese, suggests that there is potential bias in the data. Finally, there may also be a problem of simultaneity: for example, children who are not physical active are less likely to develop their motor skills (an outcome measure for 2-3 year old), but poor motor skills may also explain why some 2-3 year old are not physically active. This means that I cannot interpret any statistically-significant relationships between my independent variables and my outcome measures as being causal when a simple cross-sectional approach is taken.

4.2 Pooled Cross-sectional Regression Model

An important feature of the NLSCY is that it observes the same children over time. This means that it is possible to create a panel data set, which combines observations of children ages 2-3 in cohorts 4 and 5, along with observations of these same children at ages 4-5 and later at ages 6-7.

Importantly, this also allows me to use lagged values of the control variables in my estimating equation. This is important for two reasons. Firstly, it seems sensible to think that measured cognitive ability at time t depends not on current values of the independent variables, but on previous period values: we would expect that it is obesity at age 2 or 3 that will affect their subsequent development, and so the impact will be seen at age 4 or 5. The same is true for household income, depression, etc. Secondly, by using lagged values of control variables and independent variables, I am able to address the problem of endogeneity due to simultaneity, and make a stronger case that any statistically-significant relationships are causal.

To create the panel, I give every observation a case ID number separately at period 1, 2, 3. Then I pile these data set in one and use the id number and period to set up the panel data set; and I create lagged variables for control variables and independent variables, and run the pooled regression model. The basic relationship to be estimated can be expressed as:

$$y_{it}^{\ j} = \alpha_{it} + \beta_1 overweight_{it-1} + \beta_2 BMI^2_{it-1} + \beta_4 x_{it-1} + \varepsilon_{it} \qquad (2)$$

4.3 Fixed Effects Model

Although standa_rd and pooled cross-sectional models are simple to understand and estimate, there remain concerns with endogeneity due to omitted variables and measurement error. In particular, a problem with the pooled regression model is that it does not allow for any unobserved individual heterogeneity because it assumes that all the parameters of the model are the same across individuals. There could, however, be unobserved family-specific characteristics such as parenting style, which will impact the independent variables, such as the health condition and obesity status. Also the parenting style may also impact the children's cognitive or verbal ability scores, for example, if the parents are very strict and very concerned about children's score, they may spend a lot of time working on developing these skills in their children, and math and reading tests will become very high, regardless of whether the child is obese or not. If there is unobserved heterogeneity, the OLS estimator for the weight status will be biased and inconsistent, and thus will cause the correlation of weight status and the error term.

A standard procedure for addressing unobserved heterogeneity with panel data is to use the individual fixed effects model. To estimate this model, one wishes to have a true panel, that is, to observe the same independent and dependent variables for each individual at more than one point in time. The fixed effects estimation equation is

$$y_{it}^{j} = \alpha_f + \beta_1 overweight_{it} + \beta_2 BMI^2_{it} + \beta_3 x_{it} + \varepsilon_{it} \qquad (3)$$

Where vector α_f represents the effect of unobserved individual-observed (unobserved family characteristics independent variables) for each child. β_1 measures the causal effect of child obesity on child development and β_2 are just vectors of estimation coefficients. This model depends on the assumption that the child-specific effect are correlated with other explanatory variables.

The difficulty of using the fixed effects model with the NLSCY data set is that hyperactivity is the only outcome measure which is collected for each child at different points in time. Although hyperactivity is certainly a measure of individual health, and is known to be correlated with academic achievement (Currie & Stabile 2006), it is not itself a measure of cognitive development.

5. Regression Results

5.1 Cross-Sectional Regression Results

The results of the cross-sectional regression estimation listed in the Table 3 and reported separately for each age group. Notice that the set of outcome measures is different for each age group reflecting the fact that the NLSCY administers different tests to children of different ages. The number of observations for each age group is indicated at the bottom of the table.

Table 4 reports the coefficients of independent variables and control variables at age 2-3. Table 5 reports the results for age 4-5 and table 6 are the results for age 6-7. For the purpose of the discussion, however, I will compare the results of all of the cross-sectional estimations and focus on each of the independent variables which are significant at least at each age group.

The *overweight* dummy variable is positive and significant at 15% for PPVT-R at 4-5 year old, negative and significant for hyperactivity at 6-7 years old. But for any other output variables at other ages, this variable is not significant. At age 4-5, children who are overweight will have PPVT-R score that is 1.42 greater than do otherwise identical children who are not overweight. In table 2, it is reported that the PPVT-R score is 100.22, so an overweight child who is otherwise average would perform 0.99% better than an otherwise identical child on the PPVT-R score. At age 6-7, children who are overweight will have hyperactivity score that is 0.35 lower than do otherwise identical children who are not overweight. In table 2, it is reported that the hyperactivity score is 4.47, so an overweight child who is otherwise average would perform 7.82% worse than an identical child on the PPVT-R score.The fact that it has a positive coefficient when run the regression model with PPVT and negative when running with hyperactivity in which it has a statistically significant impact is troubling, as the expectation was that the effect would be negative and positive separately. Overall, however, the cross-sectional results seem to provide little support to the hypothesis that overweight would adversely affect cognitive outcome and positively correlated with high hyperactivity.

As explained in the data section (section 3), BMI^2 is a continuous variable, intended to capture the possibility of a non-linear effect of obesity on cognitive development. We cannot put BMI into the regression model, since it will cause highly collinearity and affect the outcome. This variable is negative and significant at the 10% level for the Ages and Stages Problem Solving score at ages 2-3, and is also negative and significant at the 5% level for the Motor Skills Development score at the same age. To understand the impact of this variable, I note that increasing BMI from 18.13 to 19.13 would increase the BMI^2 from 328.69 to 365.96, which increase by 37.26 unit. The problem solving score is 54.01, the coefficient of the variable is

-0.0003 which means the predicted score will decrease by 0.02%; average Motor Skills Development Score is 11.49 which means it will decreased by 0.09%. The coefficient of this variable is negative and significant at the 5% level when estimating with math scores for children at ages 6-7. Also when estimate with the hyperactivity-inattention score for children ages 6-7 -- an unexpected sign on the coefficient--which is -0.0007. If BMI^2 increase by one unit, the math score will decrease by 0.019 unit. The average BMI of 6-7 year old is 18.39 and the average score of math is 282.54, so an increase to 19.39 increases BMI^2 by approximately 37.39 units, and would then lower the average predicted math score by approximately 0.25%. Also if BMI increase by one unit, the hyperactivity score will decrease by 0.0007 unit. The average hyperactivity score at year 6-7 is 4.47, so a unit increase of BMI will lead to the 37.78 units of BMI^2 and would then lower the hyperactivity score by approximately 0.5%. This is not very big impact. The unexpected sign of this variable when estimating with hyperactivity seems to be at best weak evidence of a link between this variable and the cognitive outcomes measures.

I now turn to the other control variables that have a statistically significant impact in at least some of the cross-sectional regressions. The depression scores estimated coefficient is negative and significant at 5% in the equation predicting personal and hyperactivity score for children ages 2-3, also in the equation predicting “Who am I” and hyperactivity scores for children ages 4-5, and in the equation predicting prosocial scores and also hyperactivity scores for children at age 6-7. But the coefficient will also be positive and significant at 5% level in the equation predicting hyperactivity/inattention scores for children at all age. At age 2-3, children whose parents have one more point higher depression scores will have an Ages and Stages personal and hyperactivity scores which is 0.09 points lower and 0.08 higher than those children whose parents are one point below. The average Ages and Stages personal score are above 50 and this means that although the coefficients of depression scores are significant, the effect of depression scores on communication and personal or social skills are not very significant. The depression score of parent when children are at age 2-3 are 4.11 and hyperactivity scores are 3.65 at age 2-3 which means that one unit increase in depression scores, the hyperactivity scores will decrease by approximately 2%. At age 4-5, I found that children whose parents have one more point higher depression scores had 0.13 lower points in who am I scores and 0.11 higher scores in hyperactivity scores. At 6-7 years old, children whose parents have one more point higher depression scores will have 0.06 lower prosocial scores and 0.11 higher hyperactivity scores. From above, I find that the depression score of parent is highly positively correlated with hyperactivity scores.

The household income estimated coefficient is positive and significant at 5% in the equation predicting Ages and Stages communication skills for children ages 2-3, also in the equation predicting "Who am I", number knowledge, PPVT-R and hyperactivity scores for children age 4-5, and also in the equation predicting math at age 6-7. Also the coefficient of this variable is positive and only 10% significant in the equation predicting the Ages and Stages personal and motor skills scores for children age 2-3. At age 2-3, as household income increase by 1 unit, the Ages and Stages personal scores will increase by 0.56 units, the communication score will increase by 0.90 and the motor score will increase by 0.96 unit. At age 4-5, as household income increase by 1 unit, the who am I score will increase by 0.96 unit, the number knowledge score will increase by 2.80 unit, the PPVT-R score will increase by 3.30 unit, and the hyperactivity score will decrease by 0.19 unit. At age 7, as the household income increase by one unit, the math score will increase by 7.22 unit, which is a very high coefficient. From this I can find that the household income is highly correlated with the cognitive outcomes.

The parent reported health estimated coefficient is also significant in the cross-section regression model. It is significant and positive at 5% when estimating communication scores when child at age 2-3 and math scores when child at age 7, but negative and significant at 10% when estimating hyperactivity scores when child at age 2-3. At age 2-3, children who are reported good health will have 9.88 higher points in Ages and Stages problem solving scores and 1.23 lower hyperactivity scores than those children who are not reported healthy. At age 4-5, this variable is only significant at 15% when predicting the number knowledge scores which is so small. At age 6-7, children who are parent-reported good health will have 1.20 higher scores in math than children who are not reported healthy. This means only at age 2-3 and 6-7, good health has important impact on the cognitive outcome.

Birth weight also play an important role in the cognitive outcome and its estimated coefficient will be positive and significant at 5% when estimating the problem solving scores and significant at 10% when estimating the personal scores for children at age 2-3. It is also positive and significant when estimating the "Who am I" scores for children are at age 4-5 and prosocial scores for children age 6-7. At age 2-3, as the birth weight of children who are one unit heavier birthweight will have 0.29 unit higher problem solving scores and 0.13 higher personal scores than children with lighter birthweight. At age 4-5, children will get 0.76 units higher who am I scores when the birthweight increase one unit, At age 6-7, children who have one unit heavier birthweight will have 0.09 unit higher prosocial scores than other children.

The parents' education degree estimated coefficient is negative and significant at 5% when estimating motor scores for children at age 2-3, but it is positive and significant at 5% when estimating number knowledge, who am I, PPVT-R for children at age 4-5. The coefficient is negative and significant at 5% when estimating hyperactivity scores for children at age 4-5. The coefficient of this variable is also negative and significant at 5% when estimating the hyperactivity at age 6-7. Also it is negative and significant at 10% when estimating the prosocial scores. At age 2-3, children whose parent go to college will have a motor development score that is 0.39 lower than do otherwise identical children whose parents have lower education degree; they will also have 0.16 lower hyperactivity scores than other children with lower education degree parent. At age 4-5, children whose parents have college will have higher scores than other children, except for the hyperactivity scores. But strangely, children whose parents go to college will have less prosocial scores than other children at age 6-7.At this age, children whose parents go to college will also have lower hyperactivity symptoms than other children. Then I can find that when running the cross-section model, the parent education degree plays an important role in hyperactivity symptoms on children from age 4-5. Also it is positively correlated with the cognitive outcomes when children at age 4-5.

I put whether children go to nursery or not as a control variable in the period 1(age 2-3) regression model and I find that when estimating all the output variables except for the Ages and Stages communication scores, all the coefficients are significant at 5% percent. The sign of most of output variables are positive except for the hyperactivity. This means that nursery really matters to the cognitive outcome when children are at young age.

5.2 Pooled Regression Model Results

The results of the pooled cross-sectional regression estimates are reported in tables 7 (ages 4-5) and 8 (ages 6-7). The number of observations for each regression is indicated at the bottom of each table. As explained in the methodology section, I use the observed values for the independent variables in cycle t-1 to predict the dependent variable outcomes for cycle t. As a result, estimates are presented for cognitive outcomes for ages 4-5 (using the independent variables for ages 2-3) and for ages 6-7 (using the independent variables for ages 4-5). As for the cross-sectional regression estimates, the discussion below is limited to the three variables for weight (overweight, obese, and BMI^2) and to those independent variables which are statistically-significant in at least one of the regressions.

It is striking that *overweight* was not significant in the estimate for who am I scores in the cross-sectional analysis for 4-5 years old, but is significant and positive in the pooled regression model. As the pooled regression model is based on a more sensible model of the production of cognitive outcomes, this result is a bit strange. The coefficient of this variable is 0.59 which means that the overweight children will earn 0.59 unit higher Who Am I score than other children, this is a bit strange. This may because the measures of defining the overweight and obese cohorts. It is also worth remembering that *overweight* was not statistically significant for any of the cross-section estimates for 6-7 year olds, which is the same as for the pooled regression model. This suggests to me that overweight is not a concern for cognitive development of 4-5 and 6-7 years old.

My last weight variable is BMI^2, and it is not significant for the pooled regression model at 6-7, whereas it was significant for some of the estimates in the cross-sectional model. This suggests that BMI^2 at age 4-5 does not lead to low cognitive outcomes when children at age 6-7. But when estimating with number knowledge when children are 4-5, the coefficient is significant and negative. The coefficient is -0.006 which means as the BMI square increase one unit when children at age 2-3, the number knowledge score will decrease by 0.006 unit. The average BMI at age 2-3 is 18.14, as it increase one unit, the BMI square will increase by 37.44 unit. Since the average who am I score is 101.16, this means as BMI increase one unit, the number knowledge score will decrease by 0.2%. I therefore think that there is causal relationship between BMI^2 and cognitive outcome at preschool age, but do not have causal relationship at school age.

The coefficient of lagged depression score is positive and significant at 5% when estimating "Who am I" scores for children who are 4-5 years old. As the depression score of the parents when child are at 2-3 years old increase one unit, the "Who am I" scores will increase 0.03 unit separately. The coefficient of lagged household income coefficient is negative and significant when estimating with PPVT-R score. The coefficient of this variable is -1.20 which means that the household income at age 2-3 of children will negatively affect the current cognitive outcome. The sign of these two coefficients are opposite to what I expected, this may because they has correlation with other socio-demographic variable in the regression model.The coefficient of good health is not significant at any age or running with any outcome. Although it may be positive and significant when running some cross-section regression model, child's health at youth do not have impact on the cognitive outcome when children grow up.

5.3 Fixed Effects Model Results

Results for the fixed effects model are reported in table 9. The number of observations is reported at the bottom of the table. Unlike the previous models, for the fixed effects model I include only those independent and dependent variables which are observed repeatedly. This means that my only outcome measure is the hyperactivity-inattention score, and that the only independent variables are the three measures of weight (overweight, obese, BMI^2), as well as depression scores of PMK, parent-reported health and household income. As for the other regression models.

Children who have one unit higher scores in BMI square than other children will have 0.0005 higher scores in hyperactivity, this is not that significant effect. The coefficient of overweight is not significant, that means there is no association between obese status and cognitive outcomes. As the household income increase one unit, the hyperactivity score will decrease by 0.33 unit. Children who is parent-reported good health will have 1.46 lower hyperactivity/inattention points than other children who do not report good health. The coefficient of depression score is positive and also significant at 5%, which means the hyperactivity is positively correlated with the depression score.

6. Discussion and Conclusions

This study investigates the relationship between children obesity and cognitive development in young children, using three different empirical models: the cross-sectional model, the pooled regression model, and a fixed effects model. In this section, I will compare my results to those reported by other authors (as discussed earlier in my literature review). I also discuss some of the limitations of my analysis, propose avenues for future research, and discuss the policy implications of my findings.

One important difference between the approach taken here and that in other studies is the fact that I use the BMI percentile as the criterion for determining whether a child is overweight rather than the CDC cutoff. I also allow for a non-linear relationship between weight and cognitive development by including BMI squared as one of my independent variables.

My cross-sectional regression results find only weak evidence of correlation between my different measures of childhood overweight or obesity and the different measures of cognitive outcomes. My results can be compared to those of Gable, Krull and Chang (2012) and to Cawley and Spiess (2008) and of course to Carter, Dubois and Ramsey (2010), who use earlier waves of the same data set, but use changes in obesity status as an independent variable, rather than the current (or previous period) weight status. As compared to these other papers, my study finds weaker evidence of a link between childhood weight and cognitive outcomes, but for the BMI square it is highly correlated with the cognitive outcome. This may be, in part, because I did not estimate the relationship separately for boys and girls, and because I did not use changes in weight status as a control variable. Opposite to Carter et al's (2010) finding, I did not find overweight has great impact on the PPVT-R, this may because I use the standardized scores but not the raw scores, which contain much more information than do the standardized scores.

The results from the pooled regression model underscore the importance of trying to deal with potential problems of endogeneity, and in particular the problem of simultaneity. Unlike a number of other studies which use instrumental variables to overcome issues of endogeneity, my pooled regression estimates use lagged values of the independent variables to predict current values for the cognitive outcomes. In this model, the only weight variables which have statistically-significant impacts on cognitive outcomes are lagged overweight on the math scores of 6-7 year olds, and lagged BMI^2 on the pro-social score, also for 6-7 year olds. None of the weight variables were significant for the cognitive measures for 4-5 year olds. Overall, these results suggest that more attention must be given to addressing the issue of causality. In particular, since it is difficult to believe that obesity at time t causes a deterioration in cognitive development that is detectable at time t, the pooled regression results support the view that results from cross-sectional analyses should be viewed as indicative of correlation, and not causation. Of course, it is possible that the fact that I did not use changes in weight status as my independent variable may also explain why there was little impact of the weight variables on my cognitive outcome measures. Similar to Datar, Strum and Magnobosco (2004), I also find that positive relationship between overweight status and some output variables is insignificant.

A problem for my fixed-effects model is that only one outcome measure – hyperactivity-inattention - was available for all three ages, that is, for 2-3 year olds, 4-5 year olds, and 6-7 year olds; in fact, this is the only outcome measure that is observed for more than one age group. Moreover, as the NLSCY does not include siblings, I could only use the individual fixed effects model, and not the siblings fixed effects model, as in other studies such as Currie and Stabile (2006). My fixed- effects model does not have as rich a set of regressors as in other studies, and hyperactivity scores are not really a measure of cognitive development. This may explain why I did not find interesting results for the fixed effects model. Palermo and Dowd (2012) also use the fixed effects model to estimate the relationship, but they find that there is a negative association between the cognitive outcomes and overweight which is different from my outcome.

The impact of some of the other control variables is worth highlighting. For the cross-sectional model, depression scores are significant for cognitive outcome measures for hyperactivity score for all age group and some outcome measures; also it is only significant for the fixed effects model, or for the pooled regression model for 6-7 year olds. Similarly, household income is often an important factor in predicting outcomes in the cross-sectional model and fixed effects models, but lagged household income has very little impact in the pooled regression model,it is only significant and negative in estimating PPVT-R score. Birthweight matters for some of the cognitive outcome for 2-3 year olds in the cross-sectional estimates, as does whether or not a child attended nursery school, and parental education really matters for the outcome measures for 6-7 year olds. This may point to the fact that the outcome measures used in this study are typically academic achievement measures rather than purely measures of cognitive development. This is a weakness that this study shares with most of the other papers in the literature. Whether or not the parent reports that the child is in good health matters only for some output in cross-section regression model, but not in the pooled regression results; in fixed effect model, it is still significant and negative. From table 2 I find that parent- reported good health children really takes a very large proportion, which is approximately 99%, this means this variable do not have very big variance, which may affect the coefficient.

Finding about the control variables is a bit similar to above literature reviews I refer above, which states that the poor health negatively affected the cognitive outcomes. But in Salma and Schunk (2008) study they found that the child health conditions may contribute to the gaps between sociodemographic groups, this means that the household income has some correlations with the parent-reported health conditions and may be a cause of the opposite outcome we got from the regression model.

This study has a number of limitations. As acknowledged in section 5, one possible explanation for the fact that my weight variables do not always have the expected sign or a consistent pattern of significance may be that I do not use the change of weight status over time as my independent variable. It would have also been useful to check the robustness of my estimates by redoing my regressions using the change in weight status rather than current weight status as an independent variable; this would have allowed me to more directly compare my results to those papers in the literature which use the change in weight status. Also I need to think harder about how to address the problem of measurement error, since the values of many of the variables are self-reported by the parent, this may lead to some bias in the regression model.

Although I did not get the expected result, this study can also provide some reference to child health policy since childhood obesity has some effect on the cognitive output like motor or hyperactivity. So both Canadian parents and school should pay more attention to children obesity and overweight.

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8. Appendix

Table 1 VARIABLE DEFINITIONS

Variables	Definitions
Dependent variables	
Asq: problem	Ages and stages problem solving scale score
Asq: Personal	Ages and stages personal relationship scale score
Asq: communication	Ages and stages communication skills scale scores
Asq: motor	Ages and stages motor scale scores
Motor	Motor and development scale scores
PPVT-R	Peabody Picture Vocabulary Test—Revised scores
Who am I	Who am I scale scores
Number knowledge score	Number knowledge scale scores
Prosocial Behavior	Prosocial behavior scores
Math	Math scale scores
Hyperactivity	Hyperactivity inattention scores
Independent variables	
Overweight	=1 if bmi percentile is above 85 and below 95 percent
obese	=1 if bmi percentile is above 95 or equal to 85 percent
BMI square	The square of BMI
Control variables	
nursery	=1 if children has attend nursery or preschool
L.household income	Log of Total household estimated income in the past 12 months
Birth Weight	Birth weight which is reported by parents
Depression	The depression score of PMK or his/her spouse
Female	=1 if children are girl
Good health	=1 if parent-reported health is excellent/very good/good
College	=1 if PMK in the family has attend the college or above

TABLE 2: DESCRIPTIVE STATISTICS: POOLED DATA SET COHORT 4 &5 (USING LONGITUDINAL WEIGHTS)

	Age 2-3		Age 4-5		Age 6-7	
Dependent variables	Mean/ proportion	Standard deviation	Mean/ proportion	Standard deviation	Mean/ proportion	Standard deviation
Ages and Stages:asqproblem	54.01	8.58				
Asq: Personal	53.97	7.60				
Asq: communication	54.37	8.08				
Asq: motor	49.23	15.42				
Motor and development scores	11.49	2.90				
PPVT-R			102.59	14.84		
Who Am I score			24.62	6.84		
Number knowledge score			100.21	14.96		
Prosocial Behavior					14.75	3.64
Math(for 7-year-old children					283.24	41.67
Hyperactivity	3.61	2.28	4.12	2.59	4.47	3.09
Independent variables:						
Overweight	0.13		0.15		0.17	
obese	0.34		0.32		0.26	
BMI square	328.89	117.03	327.63	145.79	338.54	171.52
Control variables:						
Attend nursery Or not	0.229		0.252			
Household Income	71634.4	49855.33	78041.92	52182.22	90859.14	66191.99
Low birth Weight	3.47	0.59				
Depression	3.84	4.86	3.66	4.38	3.69	4.92
Female	0.48		0.49		0.49	
Good health	0.99		0.99		0.98	
college	0.55		0.62		0.64	
Number of observations	3107		2942		2842	

TABLE 3 CORRELATION TABLE OF THE INDEPENDENT VARIABLES AND CONTROL VARIABLES IN THE PANEL DATA SET (WEIGHTED)

	Depression	L.household income	Good health	birthweight	overweight	obese	BMI	BMI square	college
Depression	1.00								
L.household income	-0.05	1.00							
Good health	-0.03	0.05	1.00						
birthweight	0.02	-0.02	0.03	1.00					
overweight	-0.01	-0.001	0.01	-0.02	1.00				
obese	0.04	-0.09	-0.04	0.03	-0.28	1.00			
BMI	0.04	-0.07	-0.05	0.03	0.005	0.76	1.00		
BMI square	0.04	-0.07	0.05	0.03	-0.03	0.71	0.98	1.00	
college	-0.06	0.33	0.02	-0.002	0.01	-0.07	-0.08	-0.08	1.00

Table 4 CROSS SECTIONAL REGRESSION MODEL FOR 2-3 YEARS OLD (WEIGHTED)

Outcome variables	Asq: problem	Asq: personal	Asq: communication	Asq: motor	motor	Hyperactivity
Depression	0.01	-0.09***	-0.049	0.03	-0.003	0.08***
L.household income	0.52*	0.56**	0.90***	0.96**	0.36**	-0.10
good health	9.88***	0.58	3.62	5.47	0.723	-1.23**
birthweight	0.28**	0.14**	-0.0003	-0.19	0.20	0.02
overweight	0.32	0.19	-0.46	-0.809	0.08	-0.13
BMI square	-0.003*	-0.002	-0.002	-0.005	-0.002***	0.0004
college	-0.14	-0.15	0.12	-0.22	-0.39***	-0.16*
nursery	2.04***	0.99***	0.51	2.22 **	1.44***	-0.23**
Number of observations	2967					

*** means significant at 5% ** means significant at 10% * means significant at 15%

TABLE 5 CROSS SECTION REGRESSION MODEL FOR 4-5 YEARS OLD (WEIGHTED)

Outcome variables	Who am i	Number knowledge	PPVT-R	Hyperactivity
Depression	-0.11***	-0.1429*	-0.003	0.12***
L. household income	0.96***	2.80***	3.31***	-0.19***
good health	1.07	3.94*	1.15	-0.69
birthweight	0.76***	-0.07	0.014	-0.03
overweight	0.51	-1.07	1.42*	-0.15
BMI square	-0.0002	0.0008	-0.0003*	0.0001
college	1.15***	3.62***	3.45***	-0.24**
Number of observations	2920			

*** means significant at 5% ** means significant at 10% * means significant at 15%

TABLE 6 CROSS-SECTION REGRESSION MODEL FOR 6-7 YEARS OLD (WEIGHTED)

Outcome variables	Math	prosocial scores	Hyperactivity
Depression	-0.12	-0.06**	0.11***
L. household income	7.22***	-0.03	-0.15
good health	2.84 ***	0.39	-0.67
birthweight	-0.28	0.09***	-0.03
overweight	-0.23	-0.13	-0.35*
BMI square	-0.02***	0.0007	-0.0007**
college	1.05	-0.0017**	-0.49***
Number of observations	1388	2823	

*** means significant at 5% ** means significant at 10% * means significant at 15%

TABLE 7 POOLED REGRESSION MODEL FOR 4-5 YEARS OLD (WEIGHTED)

Outcome variables	WHOAMI	NUMBER KNOWLEDGE	PPVT-R
Lagged overweight	0.59**	-1.29	-0.23
Lagged BMI square	-0.001	-0.006***	-0.002
Lagged Depression	0.01 **	0.03 **	0.03
Lagged L. household income	0.01	-0.56	-1.20**
Lagged good health	-1.67	-5.39	-3.95
Number of observations	2857		

*** means significant at 5% ** means significant at 10% * means significant at 15%

TABLE 8 POOLED REGRESSION MODEL FOR 6-7 YEARS OLD (WEIGHTED)

Outcome variables	Math	Prosocial Scores
Lagged overweight	4.61	0.16
Lagged BMI square	0.004	0.0005
Lagged Depression	-0.04	-0.025
Lagged Household income	1.77	-0.03
Lagged good health	-10.50	-0.26
Number of observations	1325	2782

*** means significant at 5% ** means significant at 10% * means significant at 15%

Table 9 FIXED EFFECTS MODEL (UNWEIHTED)

Output variables:Hyperactivity/inattention		
	Coefficient	Robust standard error
overweight	-0.12	0.09
BMI squared	0.0006	0.0002***
Depression	0.004	0.00023**
Parent-reported health	-1.32	0.39***
Household income	-0.33	0.055***
Number of observations=8755		

*** means significant at 5%   ** means significant at 10%