THREE ESSAYS IN HEALTH ECONOMICS

by

Alfred Wai Ching Kong
B.A., University of British Columbia, 2004
M.A., University of Toronto, 2005

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

In the
Department of Economics
Faculty of Arts and Social Sciences

SIMON FRASER UNIVERSITY

Summer 2011

APPROVAL

Name: **Alfred Kong**

Degree: **Doctor of Philosophy**

Title of Thesis **Three Essays In Health Economics**

Examining Committee:

Chair: **Kenneth Kasa**
Professor, Department of Economics

Brian Krauth
Senior Supervisor
Associate Professor, Department of Economics

By email consultation from France

Steeve Mongrain
Supervisor
Associate Professor, Department of Economics

Stephen Easton
Supervisor
Professor, Department of Economics

Alvaro Santos Pereira
Internal Examiner
Associate Professor, Dept.of International Studies

Shinichi Sakata
External Examiner
Assistant Professor, Department of Economics
University of British Columbia

Date Approved: June 10, 2011

Declaration of Partial Copyright Licence

ABSTRACT

The first chapter of this thesis studies the relationship between obesity and school performance among children aged 16 to 17 years using data from the National Longitudinal Survey of Children and Youth (NLSCY). OLS, quantile regression and IV estimates of obesity all indicate there is a negative relationship between obesity and school performance. Quantile regression estimates indicate being obese has a strong negative impact among children at the 75th percentile for the full sample. Being obese seems to have an impact on school performance among high achievers but not among lower achievers. In addition, IV estimate of obesity indicates a strong negative effect of obesity on academic performance.

The second chapter studies the effect of retirement on various measures of health among Canadians using data from the Canadian Community Health Survey (CCHS). Both OLS regressions and a fuzzy regression discontinuity design are used to capture the effect of retirement on health. OLS estimates suggest retirement is associated with a more physically active and less stressful life among retirees in the full sample and the female subsample. On the other hand, 2SLS results from regression discontinuity design indicate retirement has a negative impact on mental health among retirees in the full sample. Retirement causes a decrease of 1.48 point (around 148% of one standard deviation) in the standardized mental health score, and the estimate is robust across different bandwidths.

The third chapter uses a linear regression model to study peer effects on adolescent weight status using data from Add Health. OLS estimates suggest the adolescent's own BMI is positively related to average peers' BMI for the female subsample. Since OLS estimates would be inconsistent if omitted variable bias exists, the linear regression model is re-estimated under different degree of correlation between the main explanatory variable and unobservable factors. Estimates under those relative correlation restrictions suggest OLS estimates are quite robust when omitted variable bias exists. The sign of estimated peer effects would only change if the correlation between the main explanatory variable and unobservable factors is as much as three times the correlation between the main explanatory variable and other controls.

DEDICATION

This thesis is dedicated to my wife, who has given me unlimited support all the time.

ACKNOWLEDGEMENTS

I would like to thank my supervisory committee. My senior supervisor, Dr. Brian Krauth, has been an excellent supervisor. His valuable advice and guidance greatly aided the completion of this thesis. Dr. Steeve Mongrain has given me lots of encouragement from the beginning to the end, and Dr. Stephen Easton has provided me with many useful comments. Their guidance, encouragement and comments were greatly appreciated.

In addition, I would like to show my gratitude to Dr. Kevin Milligan, who has helped me a lot throughout my academic career.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1:
OBESITY AND SCHOOL PERFORMANCE AMONG CHILDREN IN CANADA

1.1 Introduction

Malnutrition has long been pointed out as one of the causes of less desirable academic performance in school among children that live in poverty in developing countries (Glewwe et al., 2001 and Aldermann et al., 2006). However, until recently little has been done to study the effect of the other extreme on school outcomes: whether overnutrition (overweight or obesity) would have any effect on academic performance among children. The dramatic rise in the overweight/obesity rate among children in Canada and in US over the last 30 years has raised public concerns in recent years. In Canada, 3% and 12% of the children aged 2 to 17 years were obese and overweight respectively in 1979, yielding a combined overweight/obesity rate of 15%. The obesity rate and the overweight rate have increased to 8% and 18% respectively in 2004, yielding a combined overweight/obesity rate of 26%. About 1 in 4 children were either overweight or obese in 2004, and the numbers are expected to continue to go up in the future. In US, data from the 2002 National Health and Nutrition Examination Survey (NHANES) shows that the combined overweight/obesity rate among children aged 2 to 17 years in US was similar to that in Canada but there was a major difference in the composition of overweight and obese children between the two countries. There were fewer overweight but more obese children in US than in Canada, and the obesity rate of American girls was 13%, which was almost the double of the obesity rate of Canadian girls, which was 7% (Shields 2005).

Obesity is not only a health problem. It is normally associated with higher health risks and higher medical costs (Sinha et al., 2002 and Freedman et al., 2001). Obesity may also have an impact on a child’s life though that child’s school performance. There are several possible pathways through which obesity could affect children's school performance. Firstly, overweight/obese children might consider themselves as "outsiders" in school. They may have lower self-esteem and may consider themselves to be poorer students. This itself prevents them from succeeding in class. Secondly, absenteeism would certainly affect a student's learning in school, and overweight or obese children are more likely to miss classes (Schwimmer et al., 2003). Thirdly, being overweight or obese may be a reflection of the child's attitude towards daily life. Children who are overweight or obese may not think that personal appearances or achievements are important things in their lives; as a result, they would put little effort in maintaining a healthy weight or in doing their school work. Fourthly, obese children are more likely to suffer from sleep apnea (Kohler et al., 2009), which is the cessation of breathing during sleep. The side effects of sleep apnea include loss of memory and poor concentration. These symptoms can also lead to poor school performance.

This paper studies the effect of obesity on school performance among children aged 16 to 17 years using data from the National Longitudinal Survey of Children and Youth (NLSCY). The survey contains detailed information on characteristics of children, parents and families such as height and weight of the child, the child's score on the problem solving test, indicators of whether the child is physically active during the week, socioeconomic status of the child's family and indicators of parental input into the child's education. The depth of information provided by the NLSCY allows an instrumental variable approach in this paper that would help eliminate most, if not all, of the omitted variable bias present in previous studies.

My research contributes to four areas. First, my IV model controls for bias that is likely to be present in another study (Ding et al., 2006) that also examines the casual relationship between obesity and school performance among children using an instrumental variable approach. In Ding's study, instruments for obesity are included in the model to control for the possible unobserved heterogeneity between obese and normal-weight children. Ding et al. (2006) suggest their genetic markers are good instruments because those genetic markers are highly correlated with obesity but not with school performance. However, their instruments are likely to be correlated with an unobservable, parental input into the child's education, that could affect a child's school performance, Since children inherit their genes from their parents, parents that have "bad" genes, who have mental or physical health problems such as being overweight or obese, are more likely to have children who have those "bad" genes and health problems as well (Beardslee et al., 1998). The genetic markers would be good instruments if parents with "obese" genes have the same kind of involvement in their child's education as parents with "non-obese" genes. On the other hand, if those parents with "obese" genes behave differently than other parents in areas such as the nurture of their child, then this unobserved heterogeneity in parents' behavior would bias the results in Ding's study. My IV model tries to control for such possible bias from unobserved heterogeneity in parents' behavior by including a proxy for parental education input in the model.

Another contribution of this study is to provide evidence on the causal link between obesity and school performance among Canadian children. While Ding's study estimates the causal effect of obesity on school performance among US children, none of the studies thus far has studied the causal effect of obesity on school performance among Canadian children. One recent Canadian study (Chia 2007) only examines the association between obesity and school performance among Canadian and US children aged 10 to 14 using data from Canada and US. My instrumental variable approach allows us to establish a causal link between obesity and school performance among Canadian children.

Even though the effect of obesity on school performance may not be significant among average children, being obese might still have a significant effect on school performance among low and high achievers. Therefore, another contribution of this study is to apply a quantile regression analysis to investigate if being obese has different effects on school performance among average children, low achievers and high achievers. The fourth contribution is to examine the difference in the adverse effect of obesity on school performance among Canadian boys and girls. The combined overweight/obesity rate among children aged 2 to 17 years was similar in Canada and US. However, the obesity rate among girls aged 12 to 17 years in US was almost twice as high as that in Canada. Ding et al. (2006) suggest larger adverse effect of obesity on school performance among girls. If being obese would affect a child's learning by lowering the child's self esteem or isolating the child from his/her classmates, then the adverse effect of obesity among obese children would probably be smaller when there are more such "outsiders" in school. Since the obesity rate among Canadian girls was half of that in US, the adverse effect of obesity on school performance would probably be larger among girls in Canada.

The paper proceeds as follows. Section 2 discusses recent empirical literature on the effect of obesity on school performance among children. Section 3 provides information on the dataset and variables used in this study. My empirical strategy is described in Section 4. Results from OLS, quantile and IV regressions are presented in Section 5, and Section 6 concludes.

1.2 Review of Literature

The number of studies that examine the relationship between obesity and school performance among younger children are limited due to the lack of suitable data. Not long ago, there were few datasets available that contained children's height and weight, which help to identify overweight status, while also containing measures of school outcomes such as standardized test scores. The lack of suitable data prevented in depth investigation on this topic. Moreover, most of these datasets are cross-sectional, which prevented previous studies from looking at the causal relationship between obesity and school performance due to unobserved heterogeneity between obese and normal-weight children. Thus, most of the previous studies can only shed light on the possible association between obesity and school performance.

Mo-suwan et al. (1999) examine the relationship between obesity and academic performance among children in grade 3 to 9 using cross-sectional data from Thailand. They find a negative association between obesity and school performance among adolescents from grade 7 to 9. However, they do not find such an association exists among children from grade 3 to 6.

Using longitudinal US data, Datar and Sturm (2006) study the relationship between obesity and academic performance for those children moving from kindergarten to grade 3. They estimate the impact of being obese in grade 3 on grade 3 school outcomes, given the child overweight status in kindergarten. Their results show that for third grade girls who are not obese in kindergarten but become obese in grade 3, there is a negative association between obesity and school performance. But there is no such association between obesity and school performance among third grade boys. In addition, the magnitude of negative association between obesity and school performance among girls is small relative to other family characteristics such as mother's education and family income.

Chia (2007) studies the effect of overweight and obesity on school performance among Canadian and US children using two different longitudinal datasets from Canada and US. Chia shows that being overweight is negatively associated with academic performance among Canadian children but no such association exists among US children. Controlling for family fixed factors, an overweight Canadian child scores about 15% of one standard deviation lower in the standardized math test. On the other hand, being obese is positively associated with academic performance among US children after family fixed factors are controlled for. An obese US child scores about 15% of one standard deviation higher in the standardized math test. Chia suggests obese children might work harder than normal-weight children to compensate for the disadvantages that they face in school. Lacking the appropriate information to test this hypothesis, Chia cannot provide evidence to back up her hypothesis. Although the positive association between obesity and school performance among US children is contradictory to the hypothesis that obesity and school performance are negatively related through the four channels described in Section 1, the way that weight status affects academic performance really depends on social norms, and so may very well differ by country, age, ethnicity, social class, etc.. Thus, children in different countries could experience different impacts of obesity as Chia finds opposite effects of obesity on academic performance among Canadian and US children.

Previous studies (Mo-suwan et al., 1999, Datar and Sturm 2006, Chia 2007) that examine the relationship between weight status and school performance cannot establish any causal link between the two because those studies are restricted by the lack of exogenous variations in the data. All of the above studies show only possible association between weight status and school performance. A causal link between weight status and school performance is required for sound policymaking.

In the first study that examines whether being obese would cause the child to have poorer school performance, Ding et al. (2006) use an instrumental variables approach to estimate the effect of obesity on academic performance, where the instruments are the genes that are suggested to be associated with certain health status such as obesity and depression in biomedical literature. Their IV approach shows the impact of poor health on academic achievement is large. Both obesity and depression cause a decrease in GPA, and the 2SLS estimates are larger than the OLS estimates of obesity and depression. An obese child would have a GPA that is 0.6 point lower than a non-obese child, holding all other factors constant. The adverse effect of obesity on school outcomes among females is stronger than that among males. For the subsample of females, an obese female would have a GPA that is 0.8 point lower than a non-obese female, and the effect is statistically significant. For the subsample of males, the coefficient for obesity is close to zero and not statistically significant.

1.3 Data

I use Cycle 6 and 7 data from the National Longitudinal Survey of Children and Youth (NLSCY), which is collected by Statistics Canada, in this paper. The two cycles cover the period of 2004 to 2007. The latest two cycles are used in my study because some information is not available in earlier cycles. In addition, I restrict my sample to children who were between 16 to 17 years of age in Cycle 6 and 7 because depression score is only available for children in this age group. The depression score is included in the model to account for the relationship between depression, physical activity and school performance (Frodj et al., 2008, McKercher et al., 2009). My sample contains about 1200 observations.

The NLSCY is a longitudinal dataset which follows the same set of individuals through 1994/95 (Cycle 1) to 2006/07 (Cycle 7). Each cycle is 2 years apart. Those individuals included in the sample were aged 0 to 11 years in cycle 1 and the same set of individuals became aged 12 to 23 years in cycle 7. In latter cycles, a new sample is added to the original sample in cycle 1 to cover children aged 0 to 5 years. The survey contains detailed information on characteristics of children, parents and families such as height and weight of the child, the child's score on the problem solving test, indicators of whether the child is physically active during the week, socioeconomic status of the child's family and indicators of parental input into the child's education. The depth of information provided by the NLSCY allows an instrumental variable approach in this paper which would help eliminate most, if not all, of the omitted variable bias presented in previous studies.

The data provides information on the academic performance of a child. A problem solving test is administered for children aged 16 to 17 in cycle 6 and 7. The test is made up of 20 questions in cycle 6 and 18 questions in cycle 7. The dataset only gives the child's raw score on the test, which is the number of questions that the child answered correctly. A standardized score[1] is computed using the raw score from the data.

More importantly for this study, the data collects information about the child's height, weight and body mass index (BMI). However, the height and weight measures of a child are self-reported rather than measured in the interview. Therefore, the resulting BMI of a child calculated from self-reported height and weight might subject to some degree of inaccuracy. According to a British study which compares self-reported and measured height and weight among respondents (Spencer et al., 2001), around 22% of men and 18% of women self-reported height and weight incorrectly. Results from this study suggest self-reported measures are not perfect but are still valid to be used to determine a child's weight status. Through the BMI, a child could then be assigned a weight status in one of the following categories: normal-weight, overweight and obese. Age and gender specific cut-off points developed by the Centers for Disease Control and Prevention (CDC) are used to categorize a child's weight status[2]. Dummy variables for overweight and obesity are used in my OLS estimation. In my IV approach, an instrument for obesity is used instead.

The instrument for obesity is constructed using two physical activity indicators in the dataset. Children are asked outside of school, in the past 12 months, how often have they played sports or done physical activities[3] with or without a coach or instructor. The instrument for obesity in this study is a dummy variable, which takes on a value of 1 if children responded they have done physical activities with or without a coach as described in the above questions at least once a week in the past year outside of school. Physical activity is a good instrument for obesity because it is highly correlated with obesity. More physical activities would certainly lower the chance of being obese (Hemmingsson and Ekelund 2006), and more physical activities is positively correlated with school performance (Singh and McMahon 2006). In addition, the amount of physical activity the child does is unlikely to be associated with the innate ability of the child. The validity of the instrument is discussed in more detail in Section 4.

NLSCY provides indicators of parental input into a child's education, which could help eliminate some of the possible omitted variable bias due to unobserved parental inputs into the child's education presented in Ding's study. In NLSCY, the person most knowledgeable about the child (PMK), who is usually the child's mother, is asked whether he/she has participated in school activities such as visit the child's class, attend a school event in which the child participated, volunteer in the child's class, help in the library or computer room in the child's school, attend a parent-school meeting, participate in fund-raising event for the school or other school activities or talk to the child's teacher during the past school year. Although those indicators do not directly measure how much time did the PMK spend on the child's education, PMKs that are more active in school activities are likely to be more responsible parents and thus are also more involved in their child's education. A dummy variable for parental input into the child's education would take on a value of 1 if the PMK did one or more of the above activities during the past school year.

Dietz and Gortmaker (1985) find that more hours of television watching is associated with higher risk of being obese among children. Sharif and Sargent (2006) also suggest there is a negative relationship between media exposure and school performance.

Therefore, number of hours of television watching or video games playing on average per day and number of hours spending on a computer on average per day are included in the model to control for the possible effects of these activities on both school performance and obesity. The child's hours of work per week on average from Monday to Friday and from Saturday to Sunday are included to control for the effect of having a part time job during the week on a child's learning. To control for the popular beliefs that getting help from tutors would improve a child's academic performance, an indicator of whether the child received any tutoring help in the current school year is also included. The child's depression score is included in the model to account for the relationship between depression, physical activity and school performance (Frodj et al., 2008, McKercher et al., 2009). A higher depression score indicates the child faces more serious depression symptoms.

To control for socioeconomic differences among children, the child's age, gender and race, total household income and dummies for the highest level of education completed by the mother are included. My model also controls for the number of siblings in the household, mother's work status in the past year, single parent household and age of the mother when the child was born. Dummy variables for province of residence are also included in the model.

Descriptive statistics for the main variables in the model is presented in Table 1.1. The average BMI of the children in the sample of 1221 children aged 16 to 17 is about 22.56. Around 13.3% of the children are overweight and 7.0% of the children are obese in the sample, yielding a combined overweight/obesity rate of 21.3%. There are 541 boys in the male subsample and 680 girls in the female subsample. The prevalence of overweight is similar between the male and female subsamples, but the prevalence of obesity is higher among the male subsample. Around 8.9% of the boys are obese in the male subsample, while only 5.2% of girls are obese in the female subsample. The standardized score on the cognitive measure test has a mean that is quite closed to 0 and a standard deviation that is really close to 1. Boys in the sample perform better in the test compared with girls on average. Boys are also more physically active on average compared with girls in the sample. About 80% of the boys perform physical activities at least once a week outside of school, while around 74% of the girls do so. Overall, about 77% of the children perform physical activities at least once a week outside of school.

The education level of the mother is quite high in the sample. Around 40.5% of the mothers have a university or college degree, 9.8% of the mothers have some postsecondary education, 26.6% of the mothers have a high school diploma and 12.4% of the mothers are high school dropouts. There is no major difference in the education level of the mother between the male and female subgroups. On average, children spend 2.1 hours on TV watching per day, and boys spend slightly more hours on TV watching than girls. Quite surprisingly, children in the sample work on average 10.5 hours during the weekdays and 7 hours during the weekends for a total of 17.5 hours per week. As adults normally work around 35 to 40 hours per week, the number is pretty high since all the adolescents in the sample are still in high school. 23% of the children live with only one parent. 88.6% of the PMKs participate in at least one of the activities that might affect children's learning. The average depression score of the sample is 8.49 (maximum = 36). A higher depression score indicates the child faces more serious depression symptoms. Girls in the sample exhibit more depression symptoms than boys as they have a higher depression score. Around 90.5% of the children in the sample are white.

1.4 Methodology

The relationship between BMI and academic performance is given by the following regression model:

$$Testscore_i = \alpha_0 + \alpha_1 BMI_i + \gamma X_i' + \rho + \tau + \varepsilon_i \qquad (1)$$

$Testscore_i$ is individual i's standardized score in the problem solving test. BMI_i measures how far individual i's BMI is away from the normal BMI of 25 to control for the possible monotonic effect of BMI on $Testscore_i$. Thus, the model assumes BMI would affect school performance linearly above and below the normal BMI. X_i' are other covariates including the proxy for parental educational inputs, education level of the mother, household income, age, gender and race of the child, number of hours of television watching or video games playing on average per day, number of hours spending on computer on average per day, depression score, the number of siblings in the household, the child's hours of work per week on average from Monday to Friday and from Saturday to Sunday, an indicator of whether the child received any tutoring help in the current school year, an indicator of single parent household, age of the mother when the child was born and mother's work status in the past year. ρ represents province of residence dummies, and τ represents time dummies. The primary focus of this paper is to study the effect of obesity on school performance among children. The relationship between weight status and academic performance is given by the following regression model:

$$Testscore_i = \beta_0 + \beta_1 Obesity_i + \beta_2 Overweight_i + \gamma X_i' + \rho + \tau + \varepsilon_i \qquad (2)$$

$Testscore_i$ is individual i's standardized score in the problem solving test. $Obesity_i$ and $overweight_i$ are indicators of the weight status of individual i. X_i' are the same covariates as in equation (1), ρ represents province of residence dummies, and τ represents time dummies. Both OLS and quantile regression estimates are given by estimating equation (1) and (2).

β_1 and β_2 would capture the effect of obesity or overweight respectively on the standardized problem solving test score if $obesity_i$ and $overweight_i$ are not correlated with the error term. On the other hand, the OLS estimates of obesity and overweight would be subjected to omitted variable bias if there is any unobserved factor that affect both the weight status and test score simultaneously. For example, the innate ability of a child is unobserved. If the innate ability of a child is negatively related with the chance of being overweight or obese but positively related with test score, then the OLS estimates of obesity and overweight would be biased upward. If the innate ability of a child is positively related with the chance of being overweight or obese and also positively related with test score, then the OLS estimates of obesity and overweight would be biased downward. In addition, β_1 and β_2 actually capture the effect of any policy that affects the chance of a child being obese or overweight since $obesity_i$ and $overweight_i$ are dummy variables that can be only taking on a value of zero or one.

To remove the omitted variable bias, an instrument, which is highly correlated with obesity status but not correlated with other unobserved factors, is used in this study. To establish the causal link between obesity and academic performance, consider the following 2SLS model:

$$Testscore_i = \phi_0 + \phi_1 Obesity_i^{predicted} + \phi_2 X_i' + \rho + \tau + \upsilon_i \tag{3}$$

$$Obesity_i = \theta_0 + \theta_1 Physical\ Activity_i + \theta_2 X_i' + \rho + \tau + \mu_i \tag{4}$$

where Physical Activity in (4) is the instrument for obesity in this 2SLS model. The instrument for obesity is constructed using two physical activity indicators in the dataset.

Children are asked, outside of school, how often have they played sports or done physical activities with or without a coach or instructor in the past 12 months. The instrument for obesity in this study is a dummy variable, which takes on a value of 1 if children responded they have done those physical activities as described in the above questions at least once a week in the past year outside of school.

Physical activity is a good instrument for obesity because it is highly correlated with obesity. More physical activities would certainly lower the chance of being obese (Hemmingsson and Ekelund 2006), and more physical activities is positively correlated with school performance (Singh and McMahon 2006). For the instrument to be valid, we need the instrument to be uncorrelated with innate ability, and the instrument to affect school performance only through weight status. Gokhan et al. (1977) show there is no relationship between physical activity and cognitive functioning among children. Given the results from Gokhan's (1977) research, it is also reasonable to believe physical activity has no direct effect on school performance. One of the possible channels through which physical activity affects school performance is through weight status. The first stage regression results indicate a significant negative relationship between physical activities and obesity (coefficient of physical activity = -0.054 standard deviation = 0.020) in the data.

1.5 Results

1.5.1 OLS Results

OLS estimates of BMI are present in Table 1.2. Having a BMI that is higher than the normal BMI of 25 is negatively associated with academic performance. For the full sample, 1 unit increase of BMI above the normal BMI of 25 is associated with a decrease of 0.03 point (around 3% of one standard deviation) in the standardized score of the problem solving test. The negative effect of BMI on test score is stronger among the female subsample, and it is insignificant among the male subsample. However, compared with the effect of other variables on academic performance in the model, the impact of BMI is rather small.

OLS estimates of weight status are present in Table 1.3. Coincide with the results of Chia's study, weight status is negatively associated with academic performance among the full sample. Being overweight is associated with a decrease of 0.06 point (around 6% of one standard deviation) in the standardized score of the problem solving test, but the coefficient is not significant. Being obese is associated with a decrease of 0.16 point (around 16% of one standard deviation) in the standardized score, but the coefficient is also not significant (although it is quite close with t = -1.59).

For the female subsample, the coefficient of obesity is significant. Being obese is associated with a decrease of 0.26 point (around 26% of one standard deviation) in the standardized score of the problem solving test. For the male subsample, being obese is negatively associated with academic performance, and being overweight is positively associated with academic performance, but neither coefficient is statistically significant. The results suggest females are more sensitive to their body weight compared with males, and being obese would have a negative impact on academic performance and probably self esteem among females, but not more males.

Education level of the mother plays an important role in the academic performance of a child. Compared with children born to high school drop-out mothers, a child has a standardized score of 0.27 point higher if the mother has a university degree, 0.43 point higher if the mother has some postsecondary education for the full sample.

However, when we breakdown the full sample into two different gender subgroups, the coefficients on the education level of the mother are only significant among the male subgroup. Living in a single parent household has an impact on the child's academic performance among the full sample and the female subsample, but not among the male subsample. Living in a single parent household is associated with a decrease of 0.159 and 0.245 point in the standardized score of the problem solving test among the full sample and the female subgroup respectively. The strong negative impact of living in a single parent household is comparable to the impact of being obese among the girls. Higher level of family income is positively associated with the academic performance of the boys but not the girls. Having a working mother is positively associated with the academic performance of a girl as the girl could become more mature by taking on some of the mother's roles in the household, and more mature students might perform better in school. The age of the mother when the child was born also has a positive but very small effect on test score among girls. The coefficient of the proxy for parental educational inputs is negative but insignificant. This contradicts with the belief that more parental input into a child's education is associated with better academic performance. The proxy is constructed based on responds from parents on questions like whether he/she has participated in school activities such as visit the child's class, attend a school event in which the child participated, volunteer in the child's class, help in the library or computer room in the child's school, attend a parent-school meeting, participate in fund-raising event for the school or other school activities or talk to the child's teacher during the past school year. It could happen that parents only talk to teachers when their children do not do well in school, thus giving a negative sign to the proxy.

Age has a strong positive association with test score as older children tend to have better problem solving skills. Children who spend more time on watching TV have a lower score in the test. One unit increase in the number of hours of watching TV per day on average is associated with a 0.08 point decrease in the standardized test score among children in the full sample. However, the negative impact of TV watching is smaller among boys. In addition, time spent on computer is negatively associated with academic performance only among girls. The result could be due to the possibility that boys use computer to play video games that improve their problem solving skills while girls do not. Contrary to popular beliefs that getting help from tutors would improve a child's academic performance, children who received some tutoring help within the current school year have a standardized score which is 0.18 point less. This result could be due to the possibility that only those children who face academic problems would seek help from tutors, and those children have lower innate ability than normal children. Therefore, they do poorer in the test. Results show having a part time job would affect children's learning as children who work during the week get a lower standardized score in the problem solving test. The coefficient of the depression score has the expected negative sign but it is insignificant among the full sample. For the female subsample, 1 unit increase in the depression score is associated with a 0.02 point decrease in the standardized score of the problem solving test. The coefficient of the depression score among the male subsample is not significant.

Many of the variables in the model have significant impact on test score among the full sample, but not significant either among the male subsample or the female subsample. More importantly, the results show there is no significant impact of weight status on test score among the full sample and the male subsample. The impact of being obese is only significant among the female subsample. Those results suggest there is a difference in the way which weight status affects school performance among boys and girls. The difference could be due to the possibility that there are more obese boys than girls in a typical classroom (There are more obese boys than girls in the sample). If being obese would affect a child's learning by lowering the child's self esteem or isolating the child from his/her classmates, then the adverse effect of obesity among obese children would probably be smaller when there are more such "outsiders" in school. If there are more obese boys than girls in the classroom, obese girls are more likely to be "outsiders" in the class compared with obese boys. Thus, obese girls suffer more from being obese.

1.5.2 Quantile Regression Results

While OLS estimates examine the impact of each independent variable on test score at the mean, quantile regression method allows us to determine if being overweight or obese has different effects on school performance among average children, low achievers and high achievers by calculating regressions for different quantiles. Quantile regression estimates for the full sample and the two subsamples are presented in Table 1.4, 1.5 and 1.6 respectively. Only results from the estimation of quantile regressions at the 5^{th}, 25^{th}, 50^{th}, 75^{th} and 95^{th} conditional percentile are presented in those tables. OLS estimates are also provided in those tables to allow the direct comparison of the OLS estimates and the quantile regression estimates for each independent variables.

Interpretations of the quantile regression estimates are similar to that of the OLS estimates. The quantile regression estimate can be interpreted as the marginal change in the x^{th} conditional quantile of the dependent variable due to a marginal change in the independent variable, where as the OLS estimate shows the marginal change in the conditional mean, not quantile, of the dependent variable due to a marginal change in the independent variable. However, a child who is in the x^{th} conditional quantile will not always be in the same quantile once an independent variable changes.

There are several important differences between the OLS and the quantile regression results. The OLS estimate of obesity is negative but insignificant for the full sample. On the other hand, the quantile regression estimate indicates being obese has a strong negative impact on test score among children at the 75^{th} percentile for the full sample. However, there is no significant impact at both the lower and upper end of the distribution as well as the OLS estimates. Being obese seems to have an impact on school performance among relatively high achievers but not among lower achievers. Male students tend to do better in the test over the whole test score distribution, but the effect is stronger among high achievers. White students do significantly poorer at the median while the OLS estimate shows the effect is positive and insignificant at the mean. TV watching only has a negative impact among children in the 25^{th}, 50^{th} and 75^{th} percentile. It does not affect the top 5% and bottom 5% achievers significantly. Working during the weekdays negatively affects children's performance in the test over the entire range of the distribution, but the effect is greater among children in the 50^{th} and 75^{th} percentile. On the other hand, working during the weekends has no significant impact on children's performance in the test at the lower and upper end of the distribution, but the effect is negative and significant among children in the 25^{th}, 50^{th} and 75^{th} percentile. Only children in the 75^{th} percentile experience a negative significant impact from receiving tutoring help. This does not necessarily mean receiving tutoring help would make a child do poorer in the test, but children who receive tutoring help tend to do poorer compared with children who have similar characteristics but do not receive any tutoring help.

The effect of family income on test score is significant and positive over the whole test score distribution except for the 50th percentile. The effect is greatest among the highest achievers and lowest achievers. The education level of the mother has a positive and significant impact only among children in the 25th and 50th percentile. Unexpectedly, bottom 5% achievers indeed benefit from their single parent background. This is probably because children in single parent households are more mature, as they are more likely to look after themselves most of the time, than children who share similar characteristics but do not live in a single parent household. The age of the mother when the child was born has a positive and significant effect on test score among children in the 25th and 50th percentile only. The effect of having a working mother on test score is not significant over the entire range of the distribution, but its OLS estimate is significant. Similar to the OLS estimate, the effect of parental educational inputs is also insignificant across the conditional distribution. One thing is worth to note though: parental educational inputs have a positive impact on test score among high achievers but negative impact among low achievers. Only a proxy for parental educational inputs is used in this study[4]. The quantile regression estimates suggest parents of low achievers talk to teachers when their children do not do well in school, while parents of high achievers do so to better understand their children’s school life so that they can be more involved in their children’s learning.

For the male subsample, being overweight has a strong negative and significant impact on test score at the lower tail, while its OLS estimate is insignificant. This suggests the effect of being overweight on test score may not be constant across the conditional distribution. The education level of the mother has a positive and significant impact among boys at the upper end of the distribution, but not among low achievers. The effect of living in a single parent household on test score is very strong, negative and significant among high achievers. Similar to the estimates for the full sample, TV watching only has a negative and significant impact among boys in the 50th and 75th percentile. On the other hand, time spent on computer has a positive effect on test score among high male achievers, while the effect is insignificant among girls. The result suggests high achievers might use computer to play video games that improve their problem solving skills. Working during the weekdays has a negative impact among boys in the 25th, 50th, 75th and 95th percentile, and the effect is greater at the upper end of the distribution. In addition, working during the weekends has a negative and significant impact among boys in the 50th and 75th percentile.

For the female subsample, being obese has no significant effect among girls over the whole test score distribution, but the OLS estimate is significant. The result further suggests OLS estimates of weight status do not give the full picture of the link between weight status and school performance. In addition, the OLS estimate of the effect of living in a single parent household is also significant, but the quantile regression estimates are all insignificant. Working during the weekdays has a negative impact among girls at the lower and upper end of the distribution, while working during the weekends affects test score among girls in the 25th, 50th, 75th and 95th percentile. Receiving tutor help has a negative impact among high female achievers. Unlike the male subsample, the education level of the mother only has a positive and significant impact only among girls in the middle of the conditional distribution. The effect of the depression score is negative and significant among girls in the 5th, 25th and 50th percentile, suggesting depression affects low achievers more than high achievers among girls. The effect of family income on test score is significant and positive among girls in the 75th and 95th percentile. TV watching has a negative and significant impact among girls except for the upper end of the distribution. Time spent on computer has a negative effect on test score among girls in the 25th percentile. The result suggests high achievers might use computer to play video games that improve their problem solving skills.

1.5.3 IV Estimates

Although the OLS and quantile regression estimates of obesity show the association between obesity and school performance, they do not imply any causality between the two. To establish the causal link between obesity and school performance, an instrumental variable (IV) approach is used by estimating equation (3). IV estimates are presented in Table 1.7. The results confirm the notion that OLS estimates are biased. For the full sample, the IV estimate of obesity is strongly negative and significant. Being obese causes the child to score 2.87 points less in the standardized score of the problem solving test. However, the instrument is weak given the first stage F-statistic is less than 10 (Stock and Yogo, 2002). The weak instrument yields large standard deviation, which makes the IV estimates of obesity for the male and female subsample insignificant. The Hausman-Wu test is carried out to determine whether the dummy variable for physical activities should be treated as endogenous by testing the null hypothesis that the OLS and IV estimates are equal for the full sample. The null hypothesis cannot be rejected at the 5% level probably due to the fact that the standard deviation of the IV estimate of obesity is too big. Failing to reject the null hypothesis does not suggest there is no difference between the OLS and IV estimates. There is just not enough evidence to show there is such a difference.

For the full sample, most of the coefficients that are significant in the OLS model are still significant and have the same sign in the IV model, but the size of the coefficients change. The coefficients on the mother's education level have the same sign as the OLS estimates but become smaller. This probably indicates the weight status of a child strongly reflects how parents nurture their children. The way that parents educate their children at home determines both the weight status and academic performance of a child. The missing nurture variable creates biases in the OLS model. Unfortunately, NLSCY does not contain more explicit information on the upbringing of a child, and the proxy for parental input into the child's education used in this study is probably not a good proxy since it is insignificant. Resources should be devoted to create dataset that includes detail information on parental educational inputs and more specific measurements of the child's height and weight and physical activities done by the child would allow researchers to better estimate the casual relationship between weight status and school performance in the future.

1.6 Conclusion

This paper studies the effect of obesity on school performance among children aged 16 to 17 years using data from the National Longitudinal Survey of Children and Youth (NLSCY). OLS estimates indicate being overweight and being obese are both negatively associated with academic performance, but they are not significant among the full sample. For the male subsample, being obese is negatively associated with academic performance and being overweight is positively associated with academic performance, but both coefficients are also not significant as for the full sample. For the female subsample, being obese is associated with a decrease of 0.26 point (around 26% of one standard deviation) in the standardized score of the problem solving test. The results suggest females are more sensitive to their body weight compared with males, and being obese would have a negative impact on academic performance and probably self esteem among females. Quantile regression estimates indicate being obese has a strong negative impact at the 75th percentile for the full sample. Being obese seems to have an impact on school performance among high achievers but not among lower achievers. For the male subsample, being overweight has a strong negative and significant impact on test score at the lower tail, while its OLS estimate is insignificant. For the female subsample, being obese has no significant effect among girls over the whole test score distribution, but the OLS estimate is significant. Results suggest the effect of weight status on test score may not be constant over the entire conditional distribution. In that case, the OLS estimates would be biased. Therefore, an instrumental variable approach is used to study the causal link between obesity and school performance. IV estimate of obesity indicates a strong negative effect of obesity on academic performance. However, results from the Hausman-

Wu test suggest there is not enough evidence to show there is a difference between the OLS and IV estimates.

The coefficient of the proxy for parental educational inputs is negative but insignificant. This contradicts with the belief that more parental input into a child's education is associated with better academic performance. The result suggests the proxy may not be a good proxy. The proxy is constructed based on responds from parents on questions such as whether he/she has participated in school activities such as visit the child's class, attend a parent-school meeting or talk to the child's teacher during the past school year. It could happen that parents only talk to teachers when their children do not do well in school, thus giving a negative sign to the proxy. The difficulty of getting a good measurement of parental education inputs posts a major challenge to researchers who study anything about children that could be related to nurture and innate ability.

This paper provides further evidence on the negative relationship between weight status and school performance. However, the casual relationship between weight status and school performance remain unanswered due to the lack of good instrument for weight status. Resources should be devoted to create dataset that includes detail information on parental educational inputs and more specific measurements of the child's height and weight and physical activities done by the child would allow researchers to better estimate the casual relationship between weight status and school performance in the future.

Table 1.1: Descriptive statistics of the main variables in the model

	All Children	Male Only	Female Only
BMI	22.567	22.790	22.361
	(3.847)	(3.770)	(3.907)
Overweight	0.1333	0.137	0.130
	(0.340)	(0.344)	(0.336)
Obese	0.070	0.089	0.052
	(0.255)	(0.285)	(0.223)
Age	16.496	16.496	16.497
	(0.500)	(0.500)	(0.500)
Ln(total family income)	11.154	11.148	11.160
	(0.652)	(0.682)	(0.618)
Mother has a university degree	0.405	0.415	0.394
	(0.491)	(0.493)	(0.489)
Mother has some post-secondary education	0.098	0.092	0.104
	(0.297)	(0.289)	(0.305)
Mother is a high school graduate	0.266	0.247	0.285
	(0.442)	(0.432)	(0.452)
Mother is a high school dropout	0.124	0.129	0.119
	(0.329)	(0.335)	(0.324)
Child is a male	0.512	1	0
	(0.500)	(0)	(0)
Child is white	0.905	0.900	0.910
	(0.293)	(0.300)	(0.286)
Single parent	0.230	0.236	0.223
	(0.421)	(0.425)	(0.416)
Number of siblings living in the same household	1.237 (1.072)	1.229 (1.077)	1.245 (1.067)
Mother's age at birth	28.143	28.258	28.024
	(5.025)	(5.098)	(4.947)
Depression score	8.488	7.600	9.328
	(5.888)	(5.218)	(6.346)
Hours of TV per day on average	2.098	2.250	1.946
	(1.488)	(1.621)	(1.324)
Child's hours of work per week from Monday to Friday on average	10.543 (10.736)	12.016 (12.039)	9.253 (9.264)
Child's hours of work per week from Saturday to Sunday on average	6.996 (5.551)	7.021 (5.669)	6.973 (5.448)
Standardized problem solving test score	0.042	0.116	-0.028
	(0.995)	(1.013)	(0.972)
Parenting indicator	0.886	0.888	0.883
	(0.318)	(0.316)	(0.321)
Physical activities indicator	0.772	0.807	0.736
	(0.420)	(0.395)	(0.441)
Observations	1221	541	680

Standard deviations are in brackets.
All descriptive statistics are weighted using survey weights.

Table 1.2: OLS estimates of the relationship between BMI and school performance

	All Children	Male Only	Female Only
BMI	**-0.031****	-0.025	**-0.044*****
	(0.012)	(0.020)	**(0.016)**
Age	**0.246*****	**0.237*****	**0.242*****
	(0.053)	**(0.085)**	**(0.070)**
Ln(total family income)	**0.150****	**0.244****	0.068
	(0.059)	**(0.096)**	(0.077)
Mother has a university degree	**0.276*****	**0.402*****	0.181
	(0.096)	**(0.145)**	(0.131)
Mother has some post-secondary education	**0.439*****	**0.715*****	**0.261***
	(0.112)	**(0.182)**	**(0.147)**
Mother is a high school graduate	0.065	0.188	-0.052
	(0.095)	(0.145)	(0.129)
Hours of TV per day on average	**-0.081*****	**-0.070****	**-0.083*****
	(0.020)	**(0.029)**	**(0.030)**
Hours of computer per day on average	-0.023	-0.011	**-0.041***
	(0.015)	(0.023)	**(0.022)**
Child is male	**0.261*****		
	(0.053)		
Child is white	0.098	0.173	-0.038
	(0.116)	(0.183)	(0.160)
Single parent	**-0.151***	-0.036	**-0.240****
	(0.079)	(0.127)	**(0.104)**
Number of siblings living in the same household	-0.020	-0.059	0.009
	(0.027)	(0.050)	(0.033)
Mother's age at birth	**0.021*****	0.011	**0.028*****
	(0.005)	(0.008)	**(0.007)**
Depression score	-0.004	0.012	**-0.0157*****
	(0.004)	(0.008)	**(0.006)**
Child's hours of work per week from Saturday to Sunday on average	**-0.018*****	**-0.018****	**-0.016****
	(0.005)	**(0.007)**	**(0.007)**
Child's hours of work per week from Monday to Friday on average	**-0.016*****	**-0.010***	**-0.022*****
	(0.003)	**(0.005)**	**(0.005)**
Mother's work status	**0.223****	0.141	**0.300*****
	(0.090)	(0.152)	**(0.114)**
Tutoring	**-0.187****	-0.191	-0.127
	(0.079)	(0.141)	(0.097)
Parenting indicator	-0.135	-0.184	-0.083
	(0.0966)	(0.154)	(0.128)
Observations	1221	541	680
R^2	0.159	0.111	0.190

*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.
All regressions are weighted using survey weights.

Table 1.3: OLS estimates of the relationship between weight status and school performance

	All Children	Male Only	Female Only
Obese	-0.157	-0.155	**-0.263***
	(0.097)	(0.139)	**(0.149)**
Overweight	-0.063	0.060	-0.140
	(0.074)	(0.115)	(0.098)
Age	**0.241*****	**0.229*****	**0.239*****
	(0.053)	**(0.085)**	**(0.070)**
Ln(total family income)	**0.150****	**0.244****	0.070
	(0.059)	**(0.096)**	(0.078)
Mother has a university degree	**0.269*****	**0.397*****	0.158
	(0.096)	**(0.146)**	(0.132)
Mother has some post-secondary education	**0.434*****	**0.725*****	0.239
	(0.113)	**(0.182)**	(0.148)
Mother is a high school graduate	0.058	0.190	-0.069
	(0.095)	(0.146)	(0.130)
Hours of TV per day on average	**-0.082*****	**-0.069****	**-0.085*****
	(0.020)	**(0.029)**	**(0.030)**
Hours of computer per day on average	-0.024	-0.009	**-0.041***
	(0.015)	(0.023)	**(0.022)**
Child is male	**0.269*****		
	(0.053)		
Child is white	0.122	0.178	-0.021
	(0.116)	(0.183)	(0.160)
Single parent	**-0.159****	-0.039	**-0.245****
	(0.079)	(0.127)	**(0.105)**
Number of siblings living in the same household	-0.021	-0.055	0.007
	(0.027)	(0.050)	(0.033)
Mother's age at birth	**0.021*****	0.011	**0.028*****
	(0.005)	(0.008)	**(0.007)**
Depression score	-0.004	0.012	**-0.0155*****
	(0.005)	(0.008)	**(0.006)**
Child's hours of work per week from Saturday to Sunday on average	**-0.018*****	**-0.019****	**-0.017*****
	(0.005)	**(0.008)**	**(0.007)**
Child's hours of work per week from Monday to Friday on average	**-0.016*****	**-0.009***	**-0.022*****
	(0.003)	**(0.005)**	**(0.05)**
Mother's work status	**0.222****	0.170	**0.302*****
	(0.091)	(0.155)	**(0.115)**
Tutoring	**-0.183****	-0.184	-0.125
	(0.079)	(0.141)	(0.097)
Parenting indicator	-0.141	-0.169	-0.090
	(0.097)	(0.155)	(0.129)
Observations	1221	541	680
R^2	0.156	0.110	0.186

*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.
All regressions are weighted using survey weights.

Table 1.4: Quantile regression estimates of the relationship between weight status and school performance – All children

	Quantiles					OLS
	5%	25%	50%	75%	95%	
Obese	-0.255	0.034	-0.045	**-0.230***	0.039	-0.157
	(0.165)	(0.122)	(0.135)	**(0.125)**	(0.215)	(0.097)
Overweight	-0.128	-0.027	-0.040	-0.005	-0.111	-0.063
	(0.129)	(0.107)	(0.110)	(0.099)	(0.112)	(0.074)
Age	0.139	**0.202*****	**0.143***	**0.245*****	**0.278*****	**0.241*****
	(0.095)	**(0.076)**	**(0.074)**	**(0.079)**	**(0.076)**	**(0.053)**
Ln(total family income)	**0.229***	**0.121***	0.105	**0.152***	**0.280****	**0.150****
	(0.132)	**(0.073)**	(0.088)	**(0.076)**	**(0.114)**	**(0.059)**
Mother has a university degree	0.144 (0.164)	**0.568***** **(0.104)**	**0.497***** **(0.154)**	0.191 (0.181)	0.111 (0.160)	**0.269***** **(0.096)**
Mother has some post-secondary education	-0.101 (0.197)	**0.534***** **(0.163)**	**0.620***** **(0.183)**	0.329 (0.212)	0.282 (0.197)	**0.434***** **(0.113)**
Mother is a high school graduate	-0.105 (0.168)	**0.282**** **(0.110)**	**0.243*** **(0.144)**	0.009 (0.180)	0.090 (0.167)	0.058 (0.095)
Hours of TV per day on average	-0.070 (0.044)	**-0.087**** **(0.035)**	**-0.088***** **(0.033)**	**-0.105***** **(0.033)**	-0.023 (0.040)	**-0.082***** **(0.020)**
Hours of computer per day on average	-0.007 (0.032)	0.001 (0.022)	-0.002 (0.023)	0.022 (0.027)	0.035 (0.033)	-0.024 (0.015)
Child is male	**0.182***	**0.222*****	**0.240*****	**0.287*****	**0.279*****	**0.269*****
	(0.099)	**(0.082)**	**(0.083)**	**(0.091)**	**(0.100)**	**(0.053)**
Child is white	0.148	-0.342	**-0.345***	-0.190	-0.110	0.122
	(0.295)	(0.261)	**(0.185)**	(0.198)	(0.208)	(0.116)
Single parent	**0.329****	-0.015	-0.010	0.043	-0.128	**-0.159****
	(0.136)	(0.121)	(0.117)	(0.135)	(0.170)	**(0.079)**
Number of siblings living in the same household	-0.019 (0.054)	0.003 (0.045)	-0.007 (0.035)	0.001 (0.039)	-0.035 (0.058)	-0.021 (0.027)
Mother's age at birth	0.010	**0.020****	**0.019***	0.020	0.008	**0.021*****
	(0.011)	**(0.008)**	**(0.010)**	(0.009)	(0.009)	**(0.005)**
Depression score	-0.012	-0.010	-0.012	-0.007	-0.004	-0.004
	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)	(0.005)
Child's hours of work per week from Saturday to Sunday on average	0.006 (0.007)	**-0.020***** **(0.007)**	**-0.022***** **(0.007)**	**-0.021***** **(0.008)**	-0.013 (0.008)	**-0.018***** **(0.005)**
Child's hours of work per week from Monday to Friday on average	**-0.016**** **(0.006)**	**-0.015***** **(0.005)**	**-0.023***** **(0.005)**	**-0.020***** **(0.008)**	**-0.012*** **(0.006)**	**-0.016***** **(0.003)**
Mother's work status	0.195	0.075	0.085	0.223	-0.009	**0.222****
	(0.183)	(0.147)	(0.140)	(0.168)	(0.178)	**(0.091)**
Tutoring	-0.065	0.010	-0.125	**-0.247****	-0.169	**-0.183****
	(0.117)	(0.108)	(0.099)	**(0.110)**	(0.110)	**(0.079)**
Parenting indicator	-0.038	-0.192	-0.042	0.015	0.111	-0.141
	(0.186)	(0.123)	(0.118)	(0.151)	(0.176)	(0.097)
Observations	1221	1221	1221	1221	1221	1221
R^2	0.069	0.094	0.098	0.099	0.094	0.156

*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.

Table 1.5: Quantile regression estimates of the relationship between weight status and school performance – Male Only

	Quantiles					OLS
	5%	25%	50%	75%	95%	
Obese	-0.332	0.105	0.028	-0.245	-0.263	-0.155
	(0.231)	(0.239)	(0.198)	(0.208)	(0.256)	(0.139)
Overweight	**-0.350***	-0.131	-0.017	-0.027	-0.226	0.060
	(0.191)	(0.196)	(0.175)	(0.157)	(0.163)	(0.115)
Age	**0.345****	0.080	0.136	**0.294****	**0.226****	**0.229*****
	(0.141)	(0.111)	(0.105)	**(0.132)**	**(0.099)**	**(0.085)**
Ln(total family income)	0.309	0.092	-0.007	0.015	-0.105	**0.244****
	(0.195)	(0.143)	(0.131)	(0.130)	(0.172)	**(0.096)**
Mother has a university degree	0.326	**0.558*****	**0.613****	**0.452****	**0.535*****	**0.397*****
	(0.237)	**(0.177)**	**(0.239)**	**(0.222)**	**(0.184)**	**(0.146)**
Mother has some post-secondary education	-0.176	**0.621****	**0.701*****	0.438	**0.707*****	**0.725*****
	(0.353)	**(0.291)**	**(0.264)**	(0.280)	**(0.224)**	**(0.182)**
Mother is a high school graduate	-0.043	**0.356***	0.328	0.329	**0.386****	0.190
	(0.225)	**(0.183)**	(0.239)	(0.224)	**(0.179)**	(0.146)
Hours of TV per day on average	-0.035	-0.060	**-0.090***	**-0.089***	-0.060	**-0.069****
	(0.066)	(0.047)	**(0.047)**	**(0.051)**	(0.048)	**(0.029)**
Hours of computer per day on average	0.024	0.046	0.027	**0.088***	**0.073****	-0.009
	(0.030)	(0.033)	(0.036)	**(0.052)**	**(0.031)**	(0.023)
Child is male						
Child is white	0.177	-0.341	-0.351	-0.128	-0.313	0.178
	(0.426)	(0.494)	(0.343)	(0.335)	(0.354)	(0.183)
Single parent	0.153	0.045	-0.155	-0.236	**-0.662****	-0.039
	(0.234)	(0.234)	(0.199)	(0.212)	**(0.270)**	(0.127)
Number of siblings living in the same household	-0.063	-0.011	0.034	0.029	-0.001	-0.055
	(0.109)	(0.081)	(0.072)	(0.072)	(0.070)	(0.050)
Mother's age at birth	0.009	**0.029****	**0.030****	0.016	0.003	0.011
	(0.019)	**(0.014)**	**(0.015)**	(0.015)	(0.015)	(0.008)
Depression score	0.011	-0.001	0.011	0.017	-0.005	0.012
	(0.017)	(0.016)	(0.013)	(0.014)	(0.013)	(0.008)
Child's hours of work per week from Saturday to Sunday on average	-0.004	-0.011	**-0.025****	**-0.021***	-0.005	**-0.019****
	(0.012)	(0.011)	**(0.011)**	**(0.012)**	(0.013)	**(0.008)**
Child's hours of work per week from Monday to Friday on average	-0.011	**-0.013****	**-0.025*****	**-0.023****	**-0.020*****	**-0.009***
	(0.007)	**(0.006)**	**(0.007)**	**(0.010)**	**(0.007)**	**(0.005)**
Mother's work status	0.588	0.290	0.310	-0.097	-0.001	0.170
	(0.395)	(0.271)	(0.298)	(0.280)	(0.201)	(0.155)
Tutoring	-0.258	0.028	-0.197	-0.138	0.023	-0.184
	(0.181)	(0.226)	(0.184)	(0.243)	(0.169)	(0.141)
Parenting indicator	-0.163	-0.183	0.024	0.345	0.077	-0.169
	(0.253)	(0.174)	(0.154)	(0.221)	(0.241)	(0.155)
Observations	541	541	541	541	541	541
R^2	0.132	0.17	0.102	0.107	0.135	0.110

*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.

Table 1.6: Quantile regression estimates of the relationship between weight status and school performance – Female Only

	Quantiles					OLS
	5%	25%	50%	75%	95%	
Obese	-0.278	-0.011	-0.169	-0.199	-0.258	**-0.263***
	(0.261)	(0.165)	(0.212)	(0.192)	(0.328)	**(0.149)**
Overweight	-0.005	0.156	0.008	0.017	-0.013	-0.140
	(0.196)	(0.137)	(0.169)	(0.178)	(0.193)	(0.098)
Age	0.065	**0.209****	**0.195***	**0.271****	**0.431*****	**0.239*****
	(0.126)	**(0.100)**	**(0.117)**	**(0.106)**	**(0.120)**	**(0.070)**
Ln(total family income)	0.042	0.118	0.073	**0.264*****	**0.385*****	0.070
	(0.159)	(0.121)	(0.118)	**(0.101)**	**(0.144)**	(0.078)
Mother has a university degree	0.154	**0.468*****	**0.463****	0.096	0.175	0.158
	(0.204)	**(0.177)**	**(0.197)**	(0.201)	(0.238)	(0.132)
Mother has some post-secondary education	0.145	**0.399***	**0.476****	**0.392***	0.296	0.239
	(0.202)	**(0.237)**	**(0.232)**	**(0.230)**	(0.283)	(0.148)
Mother is a high school graduate	0.008	0.208	0.284	-0.059	0.097	-0.069
	(0.200)	(0.177)	(0.194)	(0.224)	(0.262)	(0.130)
Hours of TV per day on average	**-0.117****	**-0.142*****	**-0.126****	**-0.102***	-0.005	**-0.085*****
	(0.050)	**(0.040)**	**(0.058)**	**(0.052)**	(0.062)	**(0.030)**
Hours of computer per day on average	-0.023	**-0.081****	-0.044	-0.028	-0.001	**-0.041***
	(0.036)	**(0.039)**	(0.039)	(0.046)	(0.033)	**(0.022)**
Child is male						
Child is white	-0.238	**-0.525****	-0.190	-0.395	-0.171	-0.021
	(0.440)	**(0.253)**	(0.261)	(0.287)	(0.324)	(0.160)
Single parent	0.044	-0.122	-0.225	0.191	0.202	**-0.245****
	(0.186)	(0.171)	(0.186)	(0.223)	(0.205)	**(0.105)**
Number of siblings living in the same household	0.018	-0.023	-0.003	0.048	0.015	0.007
	(0.059)	(0.053)	(0.047)	(0.051)	(0.080)	(0.033)
Mother's age at birth	0.014	**0.020***	**0.021***	**0.028*****	-0.012	**0.028*****
	(0.016)	**(0.010)**	**(0.011)**	**(0.010)**	(0.014)	**(0.007)**
Depression score	**-0.022****	**-0.020****	**-0.019****	-0.011	-0.016	**-0.0155*****
	(0.010)	**(0.008)**	**(0.008)**	(0.009)	(0.012)	**(0.006)**
Child's hours of work per week from Saturday to Sunday on average	-0.004	**-0.026****	**-0.025****	**-0.024***	**-0.033*****	**-0.017*****
	(0.013)	**(0.010)**	**(0.010)**	**(0.011)**	**(0.011)**	**(0.007)**
Child's hours of work per week from Monday to Friday on average	**-0.022*****	**-0.021****	-0.013	**-0.022*****	**-0.026*****	**-0.022*****
	(0.007)	**(0.009)**	(0.009)	**(0.007)**	**(0.008)**	**(0.05)**
Mother's work status	-0.021	0.150	0.259	0.209	0.000	**0.302*****
	(0.158)	(0.175)	(0.177)	(0.199)	(0.265)	**(0.115)**
Tutoring	-0.175	0.093	-0.035	-0.212	**-0.384*****	-0.125
	(0.135)	(0.149)	(0.154)	(0.135)	**(0.118)**	(0.097)
Parenting indicator	0.117	-0.087	-0.110	-0.155	-0.015	-0.090
	(0.240)	(0.183)	(0.202)	(0.190)	(0.202)	(0.129)
Observations	680	680	680	680	680	680
R^2	0.107	0.107	0.108	0.129	0.144	0.186

*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.

Table 1.7: IV estimates of the relationship between obesity and school performance

	All Children	Male Only	Female Only
Obese	**-2.865***	-0.760	-21.264
	(1.595)	(1.042)	(55.757)
Age	**0.191*****	**0.209****	0.161
	(0.074)	**(0.093)**	(0.432)
Ln(total family income)	**0.151****	**0.267****	-0.416
	(0.076)	**(0.106)**	(1.359)
Mother has a university degree	0.170	**0.327***	1.038
	(0.137)	**(0.189)**	(2.393)
Mother has some post-secondary education	**0.382*****	**0.690*****	0.581
	(0.148)	**(0.192)**	(1.200)
Mother is a high school graduate	-0.037	0.148	-0.393
	(0.135)	(0.161)	(1.154)
Hours of TV per day on average	-0.026	-0.056	0.409
	(0.043)	(0.037)	(1.337)
Hours of computer per day on average	0.000	-0.008	0.149
	(0.024)	(0.023)	(0.526)
Child is male	**0.343*****		
	(0.081)		
Child is white	-0.096	0.204	-4.715
	(0.196)	(0.193)	(12.551)
Single parent	-0.021	-0.015	0.617
	(0.131)	(0.136)	(2.382)
Number of siblings living in the same household	-0.000	-0.067	0.393
	(0.037)	(0.054)	(1.052)
Mother's age at birth	0.012	0.008	0.003
	(0.008)	(0.010)	(0.079)
Depression score	-0.000	0.016	-0.027
	(0.006)	(0.011)	(0.045)
Child's hours of work per week from Saturday to Sunday on average	**-0.017*****	**-0.021****	0.075
	(0.006)	**(0.009)**	(0.247)
Child's hours of work per week from Monday to Friday on average	**-0.015*****	**-0.009***	-0.025
	(0.004)	**(0.005)**	(0.030)
Mother's work status	**0.422*****	0.220	1.214
	(0.160)	(0.191)	(2.485)
Tutoring	**-0.271****	-0.224	-0.242
	(0.114)	(0.157)	(0.633)
Parenting indicator	-0.169	-0.208	-0.043
	(0.126)	(0.164)	(0.737)
Observations	1221	541	680
First stage F statistics	3.06	2.19	3.66

*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.
All regressions are weighted using survey weights.

Endnotes

[1] The standardized problem solving test score is obtained by subtracting the child's problem solving test score with the average problem solving test score of all children who took the test in the particular cycle and then dividing the difference by the overall standard deviation of all problem solving test scores in the corresponding cycle.

[2] Cutoffs from the CDC define a child as overweight if the child's BMI is at or above the 85^{th} percentile but no more than the 95^{th} percentile, and a child is classified as obese if the child's BMI is at or above the 95^{th} percentile. For more information, see http://www.cdc.gov/obesity/childhood/index.html.

[3] Those physical activities include biking, skateboarding, hiking, skiing, camping, swimming, baseball, hockey, etc.

[4] The person most knowledgeable about the child (PMK), who is usually the child's mother, is asked whether he/she has participated in school activities such as visit the child's class, attend a parent-school meeting, talk to the child's teacher, etc. during the past school year. Although those indicators do not directly measure how much time did the PMK spend on the child's education, PMKs that are more active in school activities are likely to be more responsible parents and thus are also more involved in their child's education. A dummy variable for parental input into the child's education would take on a value of 1 if the PMK did one or more of the above activities during the past school year.

Reference List

Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long term consequences of early childhood malnutrition. Oxford Economic Papers, 58(3), 450-474.

Beardslee, W.R., et al. (1998). From cognitive information to shared meaning: Healing principles in prevention intervention. Physchiatry, 61(2), 112-130.

Behrman, J.R., & Lavy, V. (1998). Child health and schooling achievement: association, causality and household allocations. CARESS Working Papers 97-23, University of Pennsylvania.

Bjorntorp, P. 2002. Definition and classification of obesity. in Christopher G. Fairburn and Kelly D. Brownbell (eds.) eating disorders and obesity: A comprehensive handbook, 2nd Edition. (New York: Guilford Press).

Cawley, J., Meyerhoefer, C., & Newhouse, D. (2005). The impact of state physical education requirements on youth physical activity and overweight. NBER Working Paper: 11411.

Chia, Y.F. (2007). Weighty problems: An examination of childhood weight and school outcomes during puberty. Working Paper.

Currie, J. (2005). Health disparities and gaps in school readiness. Future of children, 15(1), 117-138.

Currie, J., & Stabile, M. (2005). Child mental health and human capital accumulation: The case of ADHD. NBER Working Paper: 10435.

Datar, A., Sturm, R., & Magnabosco, J.L. (2004). Childhood overweight and academic performance: National study of kindergartners and first-graders. Obesity Research, 12(1), 58-68.

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

Dietz, W.H., & Gortmaker, S.L. (1985). Do we fatten our children at the television set? Obesity and television viewing in children and adolescents. Pediatrics, 75, 807-812.

Ding, W., Lehrer, S.F., Rosenquist, J.N., & Adudrain-Mcgovern, J. (2006). The impact of poor health on education: New evidence using genetic markers. NBER Working Paper: 12304.

Duckworth, A.L., & Seligman, M.E.P. (2005). Self-discipline outdoes IQ in predicting academic performance of adolescents. Psychological Science, 16, 939-94.

Falkner, N.H., Neumark-Sztainer, D., Story, M., Jeffery, R.W., Beuhring, T., & Resnick, M.D. (2001). Social, educational, and psychological correlates of weight status in adolescents. Obesity Research, 9(1), 32-42.

Freedman, D.S., Khan, L.K., Dietz, W.H., Srinivasan, S.R., & Berenson, G.S. (2001). Relationship of childhood obesity to coronary heart disease risk factors in adulthood: The Bogalusa heart study. Pediatrics, 108, 712-718.

Frojd, S.A., & Al, E.T. (2008). Depression and school performance in middle adolescent boys and girls. Journal of Adolescence, 31(4), 485-498.

Glewwe, P., & Jacoby, H. (1995). An economic analysis of delayed primary school enrollment in a low-income country - the role of early childhood nutrition. Review of Economics and Statistics, 77, 156-169.

Glewwe, P., Jacoby, H., & King, E. (2001). Early childhood nutrition and academic achievement: A longitudinal analysis. Journal of Public Economics, 81(3), 345-368.

Gokhan, N., Binyildiz, P., Curses, C., & Arman, A. (1977). Physical ability and mental development of 9-12 age group children living in Istanbul. Journal of Sports Medicine and Physical Fitness, 17, 207-212.

Grossman, M. (1972). On the concept of health capital and the demand for health. Journal of Political Economy, 80(2), 223-255.

Hemmingsson, E., & and Ekelund, U. (2007). Is the association between physical activity and body mass index obesity dependent?. International Journal of Obesity, 31, 663-668.

Kenkel, D. (1991). Health behavior, health knowledge and schooling. Journal of Political Economy, 99(2), 287-305.

Kohler, M.J., et al. (2009). Differences in the association between obesity and obstructive sleep apnea among children and adolescents. Journal of Clinical Sleep Medicine, 5(6), 506-511.

Kremer, M., & Miguel, E. (2004). Worms: Identifying impacts on education and health in the presence of treatment externalities. Econometrica, 72(1), 159-217.

McCarthy, H.D., Cole, T.J., Fry, T., Jebb, S.A., & Prentice, A.M. (2006). Body fat reference curves for children. International Journal of Obesity, 30, 598-602.

McKercher, C.M., et al. (2009). Physical activity and depression in young adults. American Journal of Preventive Medicine, 36(2), 161-164.

Schwimmer, J.B., Burwinkle, T.M., & Varni, J.W. (2003). Health-related quality of life of severely obese children and adolescents. Journal of the American Medical Association, 289(14), 1851-3.

Sharif, I., & Sargent, J.D. (2006). Association between television, movie and video game exposure and school performance. Pediatrics, 118, 1061-1070.

Shields, M. (2005). Measured obesity, overweight Canadian children and adolescents. Statistics Canada Report, Cat. No. 82-620-MWE.

Singh, S., & McMahon, S. (2006). An evaluation of relationship between academic performance and physical fitness measures in California schools. Californian Journal of Health Promotion, 4, 207-214.

Sinha, R., et al. (2002). Prevalence of impaired glucose tolerance among children and adolescents with marked obesity. New England Journal of Medicine, 346, 802-810.

Smalley, K.J., Knerr, A.N., Kendrick, Z.V., Colliver, J.A., & Owen, O.E. (1990). Reassessment of body mass indice. American Journal of Clinical Nutrition, 52, 405-408.

Spencer, E.A., Appleby, P.N., Davey, G.K. & Key, T.J. (2001) Validity of self-reported height and weight in 4808 EPIC-Oxford participants. Public Health Nutrition, 5(4), 561-565.

Stock, J., & Yogo, M. (2002). Testing for weak instruments in linear IV regression. NBER Technical Working Paper 284.

Wellens, R.I., Roche, A.F., Khamis, H.J., Jackson, A.S., Pollock, M.L., & Siervogel, R.M. (1996). Relationships between the body mass index and body composition. Obesity Research, 4(1), 35-44.

2:
THE EFFECT OF RETIREMENT ON HEALTH[1]

2.1 Introduction

With the majority of baby boomers entering retirement within the next ten years, the financial health of Canada's public pension system in the coming future is of major concern. Future contributions to the public pension program by the labor force may not be enough to cover future payouts to retirees, which could result in either an increase in the contribution rate or a decrease in pension payments. One possible way to relieve part of this pressure on the public pension system is to make it legal for people to work beyond the conventional retirement age of 65 by banning mandatory retirement in the workplace. By allowing people to work beyond the age of 65, the contributions to the public pension program from the labor force increases, thus alleviating the financial pressure on the public pension system. However, allowing people to work beyond 65 could have implications on other public expenditures such as healthcare spending. Banning mandatory retirement in the workplace could increase healthcare spending if working makes a person's health deteriorates due to work-related stress or injuries. On the other hand, if working actually makes a person healthier as the working environment makes a person to remain mentally and physically active, then banning mandatory retirement would not only relieve pressure on the public pension system but also reduce the burden on the healthcare system.

Several studies have examined the effect of retirement on health, but the empirical findings from those studies regarding the association between retirement and different health outcomes are mixed. Using panel data from Switzerland, Mojon-Azzi et al. (2007) find retirement is associated with positive changes in self-reported health and lowers the chance of suffering from depression. However, Dave et al. (2006) suggest the contrary using panel data from US. In their fixed effects model, they control for individual fixed factors such as preference of health and human capital investment over the life-cycle, and they find retirement has a negative impact on health and physical mobility. Out of all the studies that investigate the impact of retirement on health, only a few studies examine the causal effect of retirement on health due to possible endogeneity of health in a person's retirement decision. If people that have poor health are more likely to retire earlier, there would be more retirees suffer from poor health than those who continue to work. In addition to the endogeneity problem, there are other factors that could simultaneously affect one's decision to retire and later health outcomes that would also bias the results such as personal lifestyle preferences, which is usually unobserved in the data.

Studies that attempt to disentangle the endogeneity of health in one's retirement decision using different statistical techniques find positive effects of retirement on health. Charles (2004) controls for the endogeneity of health by using a change in the US pension system, age specific retirement incentives in the US and retirement coverage as instruments to study the direct effect of retirement on psychological well-being among retirees. He finds a strong positive effect of retirement on psychological well-being, and he suggests facing less job stress is likely to be one of the reasons why retired people have better mental health. However, his approach has some potential drawbacks. Firstly, people in US know well ahead of time when they would start collecting pension payments from the government, and the change in the pension system was not unexpected. As a result, individuals may adjust their behaviors accordingly over the lifetime which might simultaneously affect their retirement decisions and later health outcomes. Secondly, the validity of the instruments as an exogenous change in retirement is also debatable. If people who have habits that adversely affect health self select into jobs with mandatory retirement, the results would be biased downward. Bound and

Waidmann (2007) use public pension eligibility as an instrument for retirement to estimate the causal effect of retirement on health. They find a small positive effect of retirement on physical health among men, but not among women. Using a method that is similar to the one applied in Charles (2004), Johnston and Lee (2009) apply a regression discontinuity design to study the impact of retirement on health. Their results suggest retirement has a positive effect on mental health and personal sense of well-being, which coincide with Charles's findings.

In this paper, we examine the causal effect of retirement on both mental and physical health by looking at health outcomes such as stress level, psychological well-being, etc. using a regression discontinuity design. This study contributes to the current literature in three ways. Firstly, we study the impact of retirement not only on mental health but also on physical health as both of these aspects of health have not been studied thoroughly in the current literature. Secondly, we examine the effect of retirement on health among Canadians. All of the studies cited previously examine the effect of retirement on health among individuals in other countries. Thirdly, our study adds to the literature by providing more evidence on the causal impact of retirement on health.

The paper proceeds as follows. Section 2 discusses the dataset and variables used in this study. Our empirical strategy is described in Section 3. Statistical results are presented in Section 4, and Section 5 concludes.

2.2 Data

This study uses data from Cycle 3.1 of the Canadian Community Health Survey (CCHS). The CCHS 3.1 is a national level cross-sectional survey that collects health information for the Canadian population in 2005. Our sample is restricted to all persons between the ages of 60 and 70 who were living in Canada during the survey. Our age restriction yields a sample of 3854. The full sample is also divided into male and female subgroups in our study. The male subgroup contains 1794 individuals, and the female subgroup contains 2060 individuals. Data from the CCHS allows a regression discontinuity approach to study the causal effect of retirement on health. The approach is discussed in more detail in section 5.

A respondent is categorized as retired if the respondent stated in the survey the main reason for not working last week was retired. As shown in Figure 1, the probability of retirement increases as an individual ages, and there is a clear discontinuity at the age of 65 for the full sample and the male subsample. Since there is no apparent reason to believe an individual's health would change greatly as he or she turns 65, we believe such a discontinuity in the probability of retirement at the age of 65 is due to the financial incentives provided by our public pension system to individuals who are at the age of 65, not because individuals suddenly become too unhealthy to work.

A number of physical and mental health measures are included in our model to capture the direct effect of retirement on an individual's health. Those health measures include self-reported measures and objective measures of health. Self-reported health measures include the self-rated general and mental health, self-perceived stress, self-reported BMI and a derived variable indicating how physically active the respondent has been. The BMI is a measure of body mass. A higher BMI indicates the respondent is less healthy. Using the self-reported BMI, the respondent is categorized as normal weight, overweight or obese. The self-rated general health score, using a scale from 0 to 4, measures the overall physical, mental and social well-being of the respondent. A higher score indicates better general health. Besides the measure of general health, a measure of mental health, using a scaled from 0 to 4, alone is also available in the data. Same as the general health score, a higher mental health score indicates better mental health. A stress score , using a scale from 1 to 5, measures the amount of stress faced by the respondent. A higher score indicates more stressful life. A physical activity index measuring how physically active the respondent has been in the past 12 months is also included as an independent variable in our model. The index is scaled from 1 to 3. A higher value suggests the respondent is less physically active. Objective measures of health include whether the respondent has a mood disorder. The value of the dichotomous variable would be 1 if the respondent has the above health problem.

Descriptive statistics for the main variables in the model is presented in Table 1. The proportion of individuals who have retired in the sample of 3854 individuals aged 60 to 70 is about 57.5%. Around 48.6% of the individuals have a university degree, around 6% of the individuals have some post secondary education, and around 14% of the individuals are high school graduates. About 39.2% of the individuals are overweight, and around 18.8% are obese. An average mental health score of 3.14 and an average general health score of 2.54, both under a scale from 0 (poor) to 4 (excellent), indicate individuals in the sample are quite healthy in general. An average physical activity index of 2.25, under a scale from 1 (active) to 3 (inactive), indicates individuals in the sample are not so active. An average stress score of 2.42, under a scale from 1 (low) to 5 (high), suggests individuals in the sample are under a certain amount of stress. The mental health score, general health score, stress score and physical activity index are standardized in the sample. About half of the individuals in the sample are males. Males and females in the sample have similar general and mental health since the two subsamples have similar general and mental health scores. However, the proportion of males that have a mood disorder is less than half of that among females. In addition, there are also more males that are overweight or obese than females.

2.3 Methodology

The following model formulates the relationship between retirement and health:

$$Health_{it} = \alpha + \beta_1 Retirement_{it} + \beta_2 Age_{it} + \beta_3 Age_{it}^2 + \delta X_{it} + \varepsilon_{it} \qquad (1)$$

In (1), $Health_{it}$ is a health measure such as physical activity index, psychological well-being, etc for individual i at time t. $Retirement_{it}$ is an indicator of retirement for individual i at time t, which takes on a value of 1 for a retired person. Age_{it} is the normalized age of the person at time t where Age = actual age of the person at time t – 65, Age_{it}^2 is the square term of Age_{it} and X_{it} is a vector of other socio-demographic characteristics such as education level of the individual and total household income, and provincial fixed-effects. The coefficient of interest is β_1 in equation (1). However, if health is endogenous to a person's retirement decision, the estimate of β_1 would be biased. In addition, if unobserved characteristics in ε_{it} simultaneously affect a person's retirement decision and health, β_1 would also be biased. The direction of the bias is unclear because, for example, if a person who is healthier is also more likely to be retired, then β_1 would be biased upwards. On the other hand, if an unhealthy person is more likely to be retired, then β_1 would be biased downwards. In Section 4, we present OLS estimates of the effect of retirement on various health measures.

As OLS estimates of β_1 in equation (1) are likely biased, we use a regression discontinuity design (RD) to estimate the causal impact of retirement on health. The RD design is a quasi-experimental design in which the treatment is only given to a group of people if they have a certain characteristic (forcing variable) that is greater than or equal to a predetermined threshold value. In our model, the forcing variable is the age of the individual. As shown in Figure 1, there is a distinct jump in the chance of retirement as an individual reaches the age of 65. We do not know exactly what causes this discontinuity in the chance of retirement at the age of 65, but we believe factors such as social norms or financial incentives provided by the Old Age Security Pension might contribute to this jump. Moreover, the validity of the RD approach does not depend on the cause of the jump, but rather on whether there is actually a jump in the chance of retirement. Our identification strategy relies on the fact that individuals are randomly assigned to treatment (retirement) around the threshold. It is true that individuals who are younger should have better health, but we only look at retirees within a certain bandwidth in our RD design. A person who is close to the normal retirement age of 65 should have similar baseline health on average as other individuals who are at 65. If those individuals at age 65 are more likely to retire than the person who is close to 65 because of social norms, financial incentives provided by the OAS pension or any other factors, we can estimate the local average treatment effect of retirement on health consistently among individuals within the bandwidth. Estimates under different bandwidths are provided in this study. A wider bandwidth would include more individuals in the sample but also increase the potential bias of the estimates. It is probably not true that people who are 60 have similar baseline health on average as other individuals who are at 65, but there should be no big difference in average baseline health between people who are 64 and 65.

There are two different types of RD designs discussed in the literature: the sharp design and the fuzzy design. In a sharp design, an individual will receive the treatment if the forcing variable is greater than or equal to the threshold value. In our context, that means the probability of retirement jump from 0 to 1 when a person reaches the age of

65. In a fuzzy design, an individual will be more likely to receive the treatment if the forcing variable is greater than or equal to the threshold value. As shown in Figure 1, approaching the age of 65 will only increase the chance of retirement discontinuously but not completely determine retirement in our study. Therefore, we have a fuzzy design. There are two assumptions that are important to the validity of our RD design. First, we assume individuals cannot exercise precise control over the forcing variable around the cutoff point (Lee and Lemieux, 2009). Since individuals cannot select their ages, it is highly likely that the first assumption is satisfied unless people lied about their ages in the survey. Second, our model assumes an individual's retirement decision at the age of 65 is a response to factors such as social norms or economic incentives provided by the OAS pension rather than a response to one's adverse health.

$$Retirement_{it} = \theta + \gamma_1 Cutoff_{it} + \gamma_2 Age_{it} + \gamma_3 Age_{it}^2 + \rho X_{it} + \tau_{it} \quad (2)$$

$$Health_{it} = \omega + \pi_1 \widehat{Retirement}_{it} + \pi_2 Age_{it} + \pi_3 Age_{it}^2 + \varphi X_{it} + \mu_{it} \quad (3)$$

Equation (2) gives the relationship between an individual's retirement decision and the OAS pension eligibility. $Retirement_{it}$ is a dichotomy variable indicates whether the individual has retired or not. $Cutoff_{it}$ is an indicator of the individual reaching the age of 65, which we observe a jump in the chance of retirement. Cutoff is equal to one if $Age_{it} \geq 0$, and 0 otherwise. Age_{it} is the normalized age of the person at time t where Age = actual age of the person at time t – 65, Age_{it}^2 is the square term of Age_{it} and X_{it} is a vector of other socio-demographic characteristics and provincial fixed-effects.

In equation (3), π_1 is a consistent estimator of the local average treatment effect of retirement on health among retirees. π_1 gives the casual effect of retirement on numerous health measures for retirees who are retired at the age of 65 due to some factors such as social norms. The main assumption for π_1 to be a consistent estimator of the effect of retirement on health is reaching the age of 65 only affects an individual's retirement decision but not his/her health. This assumption is likely to be valid because there is no reason to believe an individual's health on average would deteriorate quickly between the ages of 64 and 65, so that the individual would not be able to work by the time the individual turned 65.

There have been some discussions in the public about whether the government should raise the pension payment for retirees recently. Our results could provide some important information to policy makers regarding the issue. If retirement actually causes health of retirees to deteriorate, then raising pension payments would increase both government spending on pensions and health. In a period when our government deficits are mounting, raising pensions would then not be a wise idea. However, if retirement causes health of retirees to improve, then raising pensions would increase government spending on pensions but decrease health care spending at the same time. In this case, raising pensions might be more desirable.

2.4 Results

2.4.1. Validity of the RD design

Whether the IV results presented in this section are valid or not depend heavily on whether we have a jump in the chance of retirement at the age of 65. We test the validity of the instrument by checking whether we have a discontinuity of the treatment variable at the cutoff in the graphs and first stage F statistics in our 2SLS regressions.

Figure 2.1 is drawn using non-parametric predictions from local polynomial smoother with 95% confidence interval for the full sample, males only and females only respectively. All the figures show the proportion of individuals retired and age (age 65 is the cutoff for our forcing variable). Figures 1 shows a sharp discontinuity of the treatment variable at the cutoff among the full sample and the two subsamples. The magnitude of the discontinuity is about 18% for the full sample and the two subsamples, indicating individuals are far more likely to retire when they reach the age of 65. However, we do not know exactly what cause the jump. It could be due to the social norms or financial incentives provided by the Old Age Security pension. Nevertheless, which one of those is the true cause of the jump is not an important issue in this paper.

To test the validity of the instrument more formally, we look at first stage F statistics in our 2SLS regressions. Results from Tables 2.5 to 2.7 show the instrument is not weak as all the first stage F statistics are bigger than 10 for the full sample (Stock and Yogo 2002). The results also show the tradeoffs in IV specifications. Using a wider bandwidth increases the F statistic (thus a stronger instrument), but the standard deviation of the IV estimates would also be bigger. Our IV estimates are reliable since we do not have the weak instrument problem even with the narrowest bandwidth for the full sample. However, first stage F statistics drop below 10 when narrower bandwidths are applied for the two subsamples.

Figures 2.2 to 2.4 show the discontinuity of the outcome variables at the cutoff for the full sample and the two subsamples. There is clear discontinuity of the mental health score at the cutoff for the full sample and the male subsample. However, other health variables do not show sharp discontinuity at the cutoff.

Another assumption in our RD design is that all other covariates except for the treatment variable vary smooth around the cutoff. Figures 2.5 to 2.7 indicate education level of the individual and log total household income do not show sharp discontinuity near the cutoff. The difference in various education levels at the cutoff for the full sample and the two subsamples are all within the 95% confidence interval, further warrant the validity of our RD design.

2.4.2. OLS Results

Before we present the IV estimates, we would like to present the OLS estimates first and compare that with the IV estimates later. OLS estimates for the full sample, male subsample and female subsample are presented in Table 2.2 to 2.4 respectively.

Retirement has a significant effect only on a few health measures for the full sample. Retirement is associated with a 0.34 point decrease (around 34% of one standard deviation) in the standardized physical activity index among retirees. A lower physical activity index indicates retirees are more physically active. The fact that retirees are more physically active probably explain the reason why retirement is negative associated with the probability of being obese among retirees. Retirement is associated with a decrease of 6.7 percentage points in the probability of being obese in the full sample. However, retirement has no significant effect on the probability of being overweight. This suggests even though retirees are more physically active after retirement, they participate in physical activities that are not vigorous enough to lower BMI by a lot. Nevertheless, this is still good news to the government since our health care spending on curing heart diseases and diabetes will be lower if people retire earlier, given the results. Retirement is also associated with a decrease of 0.53 point in standardized self-perceived stress score. A lower stress score indicates retirees face less stress in life. On the other hand, retirement has no significant effect on other health measures such as mental health score, general health score and probability of suffering from mood disorders.

Gender has a significant effect on all the health measures except for mental health for the full sample. Being a male is associated with a decrease of 0.12 point in standardized self-perceived general health score. The self-rated general health score measures the overall physical, mental and social well-being of the respondent. A lower score indicates the respondent is less healthy overall. Males also feel stress is more manageable in their lives and have a lower probability of having a mood disorder. However, males are more likely to be overweight or obese even though they are more physically active according to the results. Being a male is associated with an increase of 10.5 percentage points in the probability of being overweight, and an increase of 4.5 percentage points in the probability of being obese.

An individual’s normalized age only has a marginal significant effect on mental health and the probability of having a mood disorder among retirees. One unit increase in an individual’s age beyond 65 (the cutoff) is associated with a decrease of 0.01 point in standardized self-rated mental health score and a decrease of 0.003 percentage point in the probability of having a mood disorder. A lower mental health score indicates the respondent is less mentally healthy. However, the effect is only marginal since the coefficient suggests the drop in standardized mental health score is only 1% of one standard deviation. The squared term of the normalized age only affects general health significantly, and the relationship is weak. Above results suggest that age is not a strong determinant of an individual’s health status. This further supports our choice of instrument. Age does not have a strong and significant relationship with the health measures used in this study, but it is a strong determinant of whether the retiree receives the OAS pension, which affects an individual’s choice of when to retire.

Socioeconomic status has a significant effect on health status. An individual’s education level has a significant positive relationship with both mental and general health status of the individual. Compared with high school dropouts, being a high school graduate is associated with a 0.16 point in standardized mental health score and 0.29 point increase in standardized general health score. The positive effect of education on health is even greater for a person obtained higher education. Having a university degree is associated with a 0.22 point and 0.30 point increase in standardized mental health score and standardized general health score respectively. In addition, individuals with higher education level are also more physically active compared with high school dropouts. University graduates also have a lower chance of suffering from mood disorders and being obese. Higher total family income is associated with better mental and general health and also lowers the chance of having a mood disorder or being obese.

Retirement has a stronger effect on various health measures among male retirees compared with the full sample. Retirement is associated with poorer general health among male retirees. Male retirees have a lower standardized general health score compared with male workers. The deterioration in general health might be due to the lack of a sense of accomplishment among male retirees. They have been the main breadwinners in their families for a long time; it is probably hard for them to step down from the role. However, it is impossible for us to test this hypothesis using the data. Moreover, results show male retirees are more physically active, have lower stress level and have a lower chance of being obese, suggesting better mental and physical health after retirement among male retirees. Age has a marginal effect on mental health among males. In addition, males are less physically active as they age. Higher total household income level and higher education level are associated with better mental and general health.

For the female subsample, retirement has a weaker positive effect on standardized physical activity index and standardized stress score compared with the male subsample.

Female retirees are more physically active than female workers, and female retirees have lower stress level. Age and its squared term again have a marginal effect, if significant, on mental and physical health among females. Education level has a stronger positive effect on health among females compared with males. Similar with the male subsample, the effect of income level on health is also positive.

2.4.3. IV Results

Because of the possible endogeneity problem between retirement and health and omitted variables bias, OLS estimates can only shed light on the possible association between retirement and health. Therefore, OLS is not the preferred specification in our study. In this section, we will present our 2SLS results which show the casual relationship between retirement and health.

Our IV estimates, which are presented in Tables 2.5 to 2.7, show a totally different picture compared with the OLS estimates. The OLS estimates suggest there is no association between retirement and mental health, however, IV estimates show there is a strong and significant relationship between retirement and mental health. Retirement causes standardized self-rated mental health score to decrease by 1.30 to 1.74 point, depending on the chosen bandwidth. The estimate is robust across different bandwidths, including the optimal bandwidth suggested by Imbens and Lemieux (2008) for the full sample. Using the optimal bandwidth, retirement causes standardized self-rated mental health score to decrease by 1.48 point for the full sample. For the male subsample, the effect of retirement on mental health is also positive and strong, but the estimate is significant under only two of the bandwidths.

Retirement also has a strong positive and significant effect on the probability of having a mood disorder among retirees in the full sample. Retirement reduces the probability of having a mood disorder by about 30 percentage points, which is far greater than the effect suggested by OLS estimates. However, the result is quite sensitive to the bandwidth chosen, and the estimate become really close to zero and insignificant when the optimal bandwidth is used. The estimates for other health measures are not significant for the full sample and the two subsamples. In addition, our results from the regression discontinuity approach are showing the immediate effect of retirement on health only. Even though a retiree has poorer mental health right after retirement, there is a possibility that his/her mental health condition would improve once the retiree adapts to his/her retirement life.

Given our results, retirement actually causes a retiree's mental health to deteriorate. Therefore, the removal of mandatory retirement would slow down the deterioration of mental health among workers who choose to work beyond the regular retirement age, therefore relieving some pressure on our health care system and our government balance sheet. In addition, if financial incentives provided by the OAS pension is the true cause of the jump in the chance of retirement at the age of 65, then a probable future policy of raising pensions would do more harm than good to Canada. Raising pensions not only speed up the deterioration of mental health among workers who are induced to retire because of the increased financial incentives provided by the OAS pensions, which requires more resources for mental health care thus increasing heath care spending. It also put more financial pressure on our increasingly fragile pension system. Such an increase in pensions would require not only higher contributions from workers to fund the increase in pensions, but also higher taxes to fund the increase in health care spending. At a time when most of the governments in the world are trying to reduce government deficits, such a move to raise pensions is not appropriate at the moment.

2.5 Conclusion

In this paper, we have studied the effect of retirement on various measures of health. We have used OLS regressions and a fuzzy regression discontinuity design to capture the effect of retirement on health. OLS estimates suggest retirement is associated with a more physically active and less stressful life among retirees in the full sample and the female subsample. However, retirement is also associated with deterioration in general health among male retirees. Because of the possible endogeneity problem between retirement and health and omitted variables bias, OLS estimates can only show the possible association between retirement and health.

With a fuzzy regression discontinuity design, we have investigated the local average treatment effect of retirement on health among retirees. Our RD results indicate retirement has a strong negative impact on mental health, but the effect on general health is not significant. Using the optimal bandwidth, retirement causes standardized self-rated mental health score to decrease by 1.48 point (around 148% of one standard deviation) for the full sample, and the estimate is also robust across different bandwidths. Even though our LATE estimates only show the casual relationship between retirement and health among retirees around the cutoff of 65, there are only 40 percent of the workers retired before the age of 60. Therefore, our results might still have general implications among the whole population.

Given our results, retirement actually causes a retiree's mental health to deteriorate. Therefore, the removal of mandatory retirement would slow down the deterioration of mental health among workers who choose to work beyond the regular retirement age, therefore relieving some pressure on our health care system and our government balance sheet. In addition, if financial incentives provided by the OAS pension is the true cause of the jump in the chance of retirement at the age of 65, then a probable future policy of raising pensions would do more harm than good to Canada. Raising pensions not only could speed up the deterioration of mental health among workers who are induced to retire because of the increased financial incentives provided by the OAS pensions, which requires more resources for mental health care thus increasing heath care spending. It also put more financial pressure on our increasingly fragile pension system. Such an increase in pensions would require not only higher contributions from workers to fund the increase in pensions, but also higher taxes to fund the increase in health care spending. At a time when most of the governments in the world are trying to reduce government deficits, such a move to raise pensions is not appropriate at the moment.

We have shown the casual relationship between retirement and mental health in this study. However, our data lacks a more specific measure of physical health which prevents us to establish a link between retirement and physical health in this paper. Hopefully, future waves of CCHS would include physical health measures so that researchers can measure the effect of retirement on physical health specifically among Canadian retirees. In addition, our LATE estimates only show the casual relationship between retirement and health among retirees around the cutoff of 65. Therefore, our results might or might not have general implications among retirees between ages 60 and 70. Larger sample size would allow more general applications of LATE estimates.

Table 2.1: Descriptive statistics of the main variables in the model

	Full sample	Male Only	Female Only
Retired	0.575	0.492	0.655
	(0.494)	(0.500)	(0.476)
Age	64.533	64.411	64.651
	(3.153)	(3.078)	(3.221)
Ln(total family income)	10.664	10.788	10.514
	(0.852)	(0.882)	(0.789)
Has a university degree	0.486	0.524	0.450
	(0.500)	(0.500)	(0.498)
Has some post-secondary education	0.059	0.054	0.063
	(0.235)	(0.226)	(0.243)
Is a high school graduate	0.142	0.118	0.165
	(0.349)	(0.322)	(0.372)
Male	0.490	1	0
	(0.500)	(0)	(0)
Mental Health Score	0.054	0.054	0.055
	(0.981)	(0.978)	(0.985)
General Health Score	0.067	0.054	0.080
	(0.985)	(0.987)	(0.983)
Has a mood disorder	0.039	0.023	0.055
	(0.194)	(0.150)	(0.227)
Stress Score	0.052	-0.009	0.110
	(0.994)	(1.037)	(0.947)
Physical Activity Index	-0.038	-0.106	0.027
	(1.002)	(1.025)	(0.976)
Is overweight	0.392	0.447	0.339
	(0.488)	(0.497)	(0.474)
Is obese	0.188	0.209	0.166
	(0.390)	(0.407)	(0.373)
Observations	3854	1794	2060

Standard deviations are in brackets.
All descriptive statistics are weighted using survey weights.

Table 2.2: OLS Estimates – Full Sample

	Mental Health	General Health	Physical Activity Index	Mood Disorder	Stress	Obese
Retired	-0.007	-0.066	-0.344***	0.003	-0.531***	-0.067***
	(0.043)	(0.042)	(0.044)	(0.009)	(0.043)	(0.018)
Age	-0.015***	-0.009	0.009	-0.003**	-0.003	-0.003
	(0.007)	(0.006)	(0.007)	(0.001)	(0.007)	(0.003)
Age Squared	0.001	-0.003*	0.001	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)
Male	-0.048	-0.122***	-0.167***	-0.032***	-0.203***	0.045***
	(0.039)	(0.038)	(0.040)	(0.008)	(0.039)	(0.016)
University Degree	0.218***	0.304***	-0.345***	-0.0178*	-0.035	-0.065***
	(0.046)	(0.044)	(0.047)	(0.009)	(0.046)	(0.019)
Some Post-secondary	0.020	0.332***	-0.202**	-0.005	0.075	-0.031
	(0.083)	(0.079)	(0.084)	(0.017)	(0.082)	(0.034)
High School Graduate	0.156***	0.288***	-0.254***	0.007	-0.010	-0.031
	(0.062)	(0.060)	(0.063)	(0.012)	(0.062)	(0.025)
Log(total family income)	0.165***	0.173***	-0.026	-0.009*	0.033	-0.031***
	(0.024)	(0.023)	(0.024)	(0.005)	(0.024)	(0.010)
Observations	2590	2625	2590	2627	2620	2628
R^2	0.048	0.072	0.061	0.020	0.087	0.029

Note: Provincial dummies are also included in the model.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.

Table 2.3: OLS Estimates – Male Only

	Mental Health	General Health	Physical Activity Index	Mood Disorder	Stress	Obese
Retired	-0.023	-0.127**	-0.444***	0.014	-0.538***	-0.094***
	(0.060)	(0.058)	(0.063)	(0.009)	(0.061)	(0.025)
Age	-0.016*	-0.012	0.017*	-0.001	0.008	0.000
	(0.010)	(0.009)	(0.010)	(0.001)	(0.010)	(0.004)
Age Squared	-0.002	0.001	-0.002	-0.001	0.004	0.001
	(0.003)	(0.003)	(0.003)	(0.000)	(0.003)	(0.001)
Male						
University Degree	0.216***	0.180***	-0.285***	-0.012	0.007	-0.071***
	(0.065)	(0.063)	(0.069)	(0.010)	(0.067)	(0.027)
Some Post-secondary	-0.072	0.044	-0.258**	0.007	0.209*	0.012
	(0.124)	(0.120)	(0.131)	(0.019)	(0.126)	(0.052)
High School Graduate	0.269***	0.197**	-0.236**	0.018	0.077	-0.036
	(0.091)	(0.088)	(0.096)	(0.014)	(0.094)	(0.039)
Log(total family income)	0.159***	0.156***	-0.025	-0.006	0.065*	-0.027**
	(0.032)	(0.032)	(0.034)	(0.005)	(0.033)	(0.014)
Observations	1299	1322	1298	1324	1321	1325
R^2	0.056	0.070	0.067	0.015	0.102	0.039

Note: Provincial dummies are also included in the model.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.

Table 2.4: OLS Estimates – Female Only

	Mental Health	General Health	Physical Activity Index	Mood Disorder	Stress	Obese
Retired	-0.010	-0.007	-0.194***	-0.008	-0.511***	-0.024
	(0.065)	(0.061)	(0.063)	(0.016)	(0.062)	(0.025)
Age	-0.013	-0.004	-0.000	-0.005**	-0.012	-0.006*
	(0.009)	(0.009)	(0.009)	(0.002)	(0.009)	(0.004)
Age Squared	0.004	-0.007**	0.005*	0.001	-0.003	0.002*
	(0.003)	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)
Male						
University Degree	0.232***	0.435***	-0.399***	-0.023	-0.072	-0.054**
	(0.066)	(0.063)	(0.064)	(0.016)	(0.063)	(0.025)
Some Post-secondary	0.108	0.612***	-0.149	-0.018	-0.047	-0.064
	(0.111)	(0.105)	(0.107)	(0.027)	(0.106)	(0.043)
High School Graduate	0.044	0.386***	-0.249***	-0.004	-0.086	-0.016
	(0.085)	(0.080)	(0.083)	(0.021)	(0.081)	(0.033)
Log(total family income)	0.167***	0.180***	-0.038	-0.010	-0.011	-0.035**
	(0.036)	(0.034)	(0.035)	(0.009)	(0.035)	(0.014)
Observations	1291	1303	1292	1303	1299	1303
R^2	0.048	0.097	0.061	0.019	0.076	0.032

Note: Provincial dummies are also included in the model.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.

Table 2.5: IV Estimates of the Relationship Between Retirement and Health – Full Sample

Health Measures	Bandwidth				
	(A) 5	(B) 4	(C) 3	(D) Optimal	Optimal Bandwidth
Mental Health	-0.678 (0.696) [37.89]	**-1.296*** **(0.792)** [15.27]	**-1.739*** **(0.925)** [10.02]	**-1.477***** **(0.520)** [6.27]	1.689
General Health	0.104 (0.579) [37.66]	0.385 (0.640) [15.77]	0.273 (0.676) [10.52]	-2.728 (2.230) [9.38]	2.468
Physical Activity Index	-0.089 (0.683) [37.75]	-0.262 (0.690) [15.20]	-0.942 (0.751) [10.01]	0.103 (1.136) [9.51]	2.756
Mood Disorder	-0.162 (0.128) [37.65]	**-0.293*** **(0.156)** [15.82]	**-0.343*** **(0.188)** [10.58]	0.002 (0.097) [6.24]	1.583
Stress	0.387 (0.640) [37.49]	0.106 (0.652) [15.77]	0.749 (0.825) [10.56]	0.517 (0.737) [10.12]	2.743
Obese	0.284 (0.261) [37.72]	0.231 (0.271) [15.82]	0.202 (0.289) [10.58]	-0.247 (0.714) [8.77]	2.062

Note: Numbers in column (A) to (D) are estimates of π_1 in equation (3). Other control variables included are: Age and age squared, gender, education level, logarithm of total family income and provincial dummies.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.
First stage F statistics are in square brackets.

Table 2.6: IV Estimates of the Relationship Between Retirement and Health – Male Only

Health Measures	Bandwidth				
	(A) 5	(B) 4	(C) 3	(D) Optimal	Optimal Bandwidth
Mental Health	-1.891 (1.499) [19.98]	-2.008 (1.243) [7.43]	**-1.572*** **(0.828)** [5.09]	**-1.923**** **(0.876)** [5.21]	3.117
General Health	0.735 (0.981) [19.79]	0.554 (0.864) [7.70]	0.873 (0.714) [5.36]	-0.954 (0.736) [5.44]	3.104
Physical Activity Index	0.190 (1.239) [19.78]	-0. 101 (0. 931) [7.35]	-1.085 (0. 692) [5.08]	-0.817 (0.708) [3.49]	2.363
Mood Disorder	-0.346 (0.212) [19.77]	-0.171 (0.161) [7.73]	-0.200 (0.140) [5.39]	-0.012 (0.086) [2.01]	1.931
Stress	0.726 (1.097) [19.60]	0. 443 (0. 901) [7.64]	0. 887 (0. 825) [5.39]	0.782 (0.797) [5.55]	3.105
Obese	0.640 (0.505) [19.86]	0.101 (0.352) [7.73]	0.082 (0. 284) [5.39]	0.309 (0.328) [3.83]	2.392

Note: Numbers in column (A) to (D) are estimates of π_1 in equation (3). Other control variables included are: Age and age squared, education level, logarithm of total family income and provincial dummies.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.
First stage F statistics are in square brackets.

Table 2.7: IV Estimates of the Relationship Between Retirement and Health – Female Only

Health Measures	Bandwidth				
	(A) 5	(B) 4	(C) 3	(D) Optimal	Optimal Bandwidth
Mental Health	0.555 (0.819) [18.41]	-0.191 (1.042) [6.47]	-4.415 (10.02) [4.25]	-7.344 (23.348) [3.96]	2.688
General Health	-0.194 (0.739) [17.84]	0.364 (1.003) [6.44]	-4.170 (7.940) [4.17]	10.503 (34.238) [3.10]	2.311
Physical Activity Index	-0.365 (0.775) [18.43]	-0.856 (1.072) [6.47]	-0.322 (4.646) [4.25]	-8.232 (26.480) [3.27]	2.354
Mood Disorder	-0.009 (0.189) [17.84]	-0.477 (0.324) [6.44]	-1.498 (2.762) [4.17]	-2.111 (7.493) [2.94]	2.015
Stress	-0.091 (0.745) [17.80]	-0.757 (1.002) [6.46]	0.655 (4.373) [4.19]	-6.058 (22.155) [4.21]	3.087
Obese	-0.100 (0.300) [17.84]	0.476 (0.443) [6.44]	1.232 (2.443) [4.17]	-3.228 (10.502) [3.04]	2.233

Note: Numbers in column (A) to (D) are estimates of π_1 in equation (3). Other control variables included are: Age and age squared, education level, logarithm of total family income and provincial dummies.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are in brackets.
F statistics are in square brackets.

Figure 2.1: Test of the Discontinuity of the Treatment Variable at the Cutoff

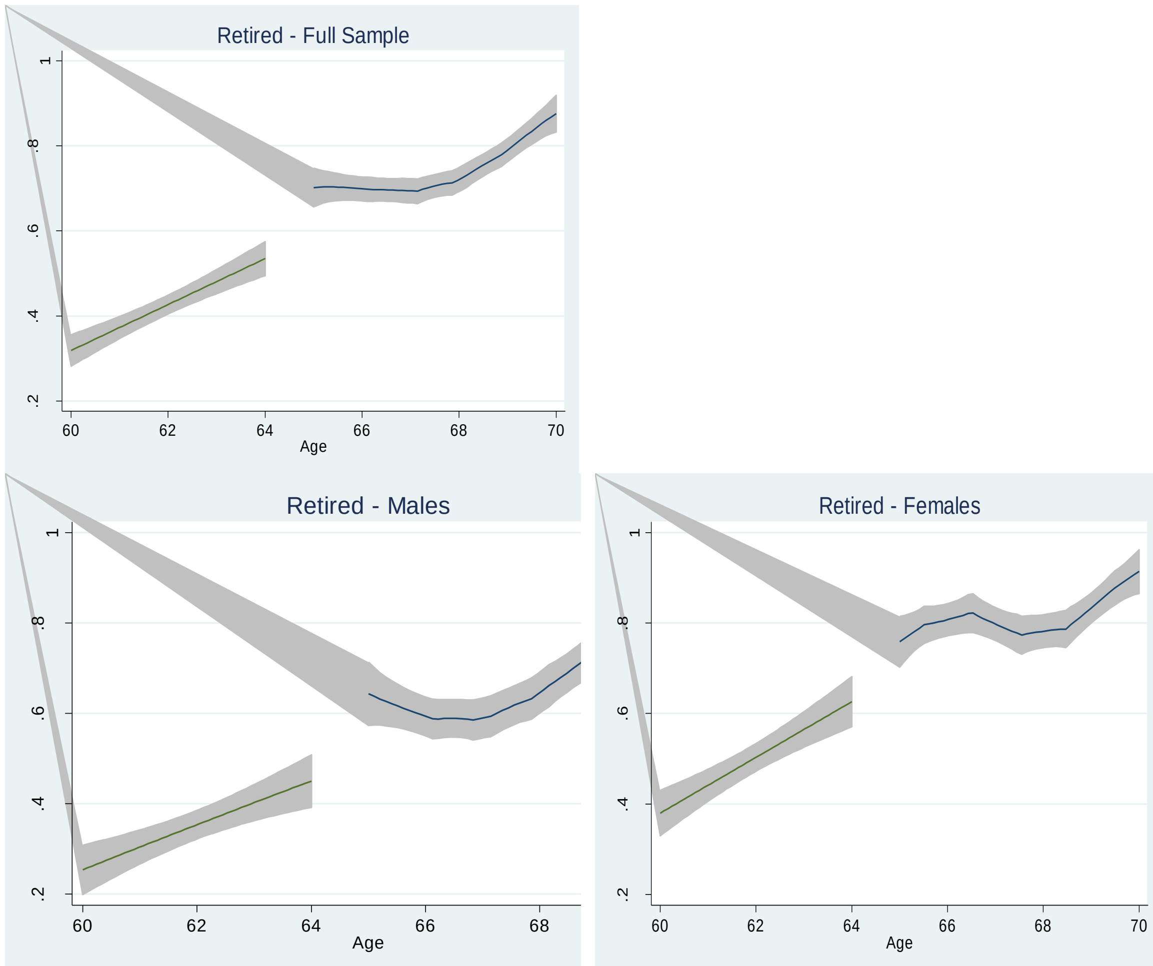


Figure 2.2: Test of the Discontinuity of the Outcome Variables at the Cutoff – Full Sample

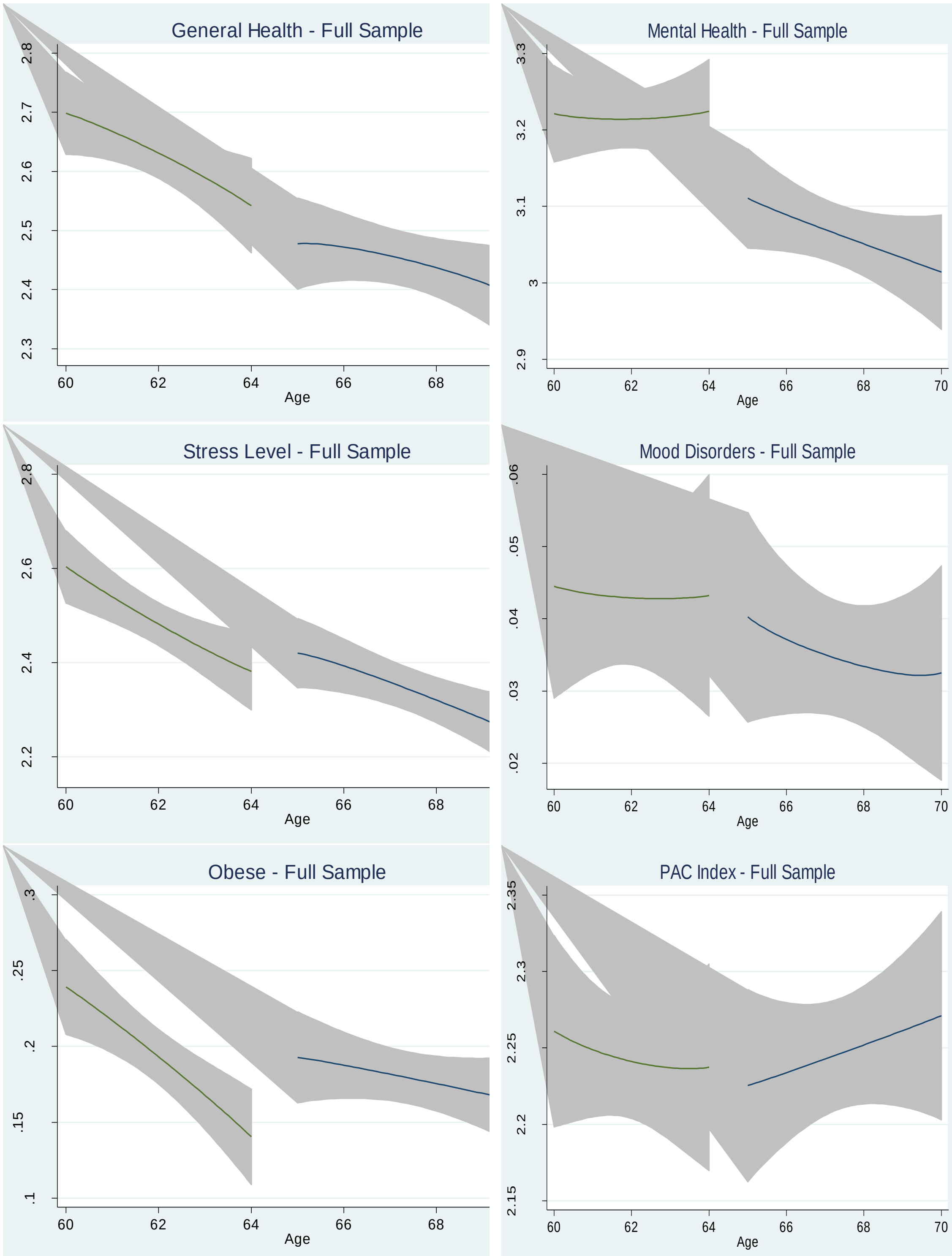


Figure 2.3: Test of the Discontinuity of the Outcome Variables at the Cutoff – Male Only

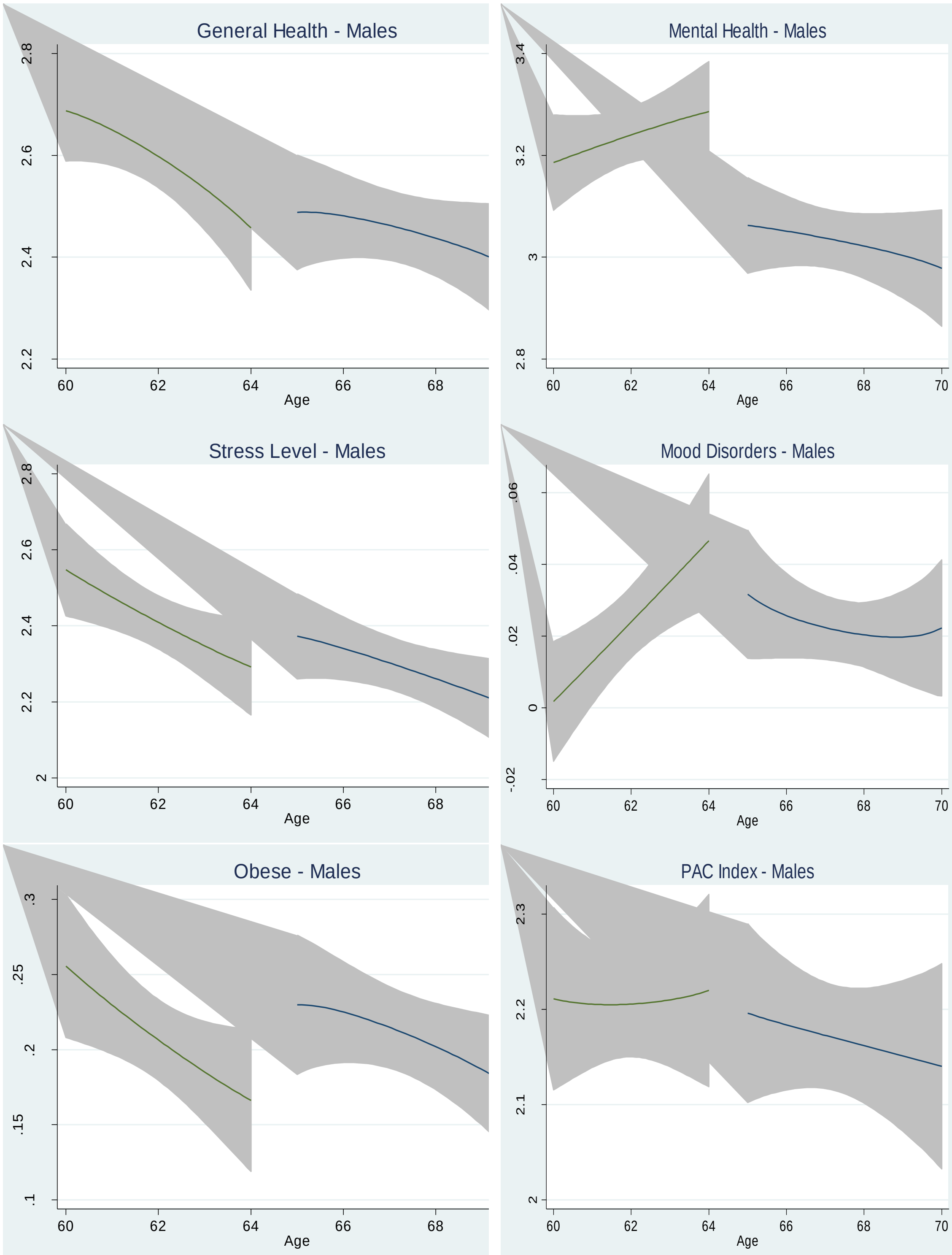


Figure 2.4: Test of the Discontinuity of the Outcome Variables at the Cutoff – Female Only

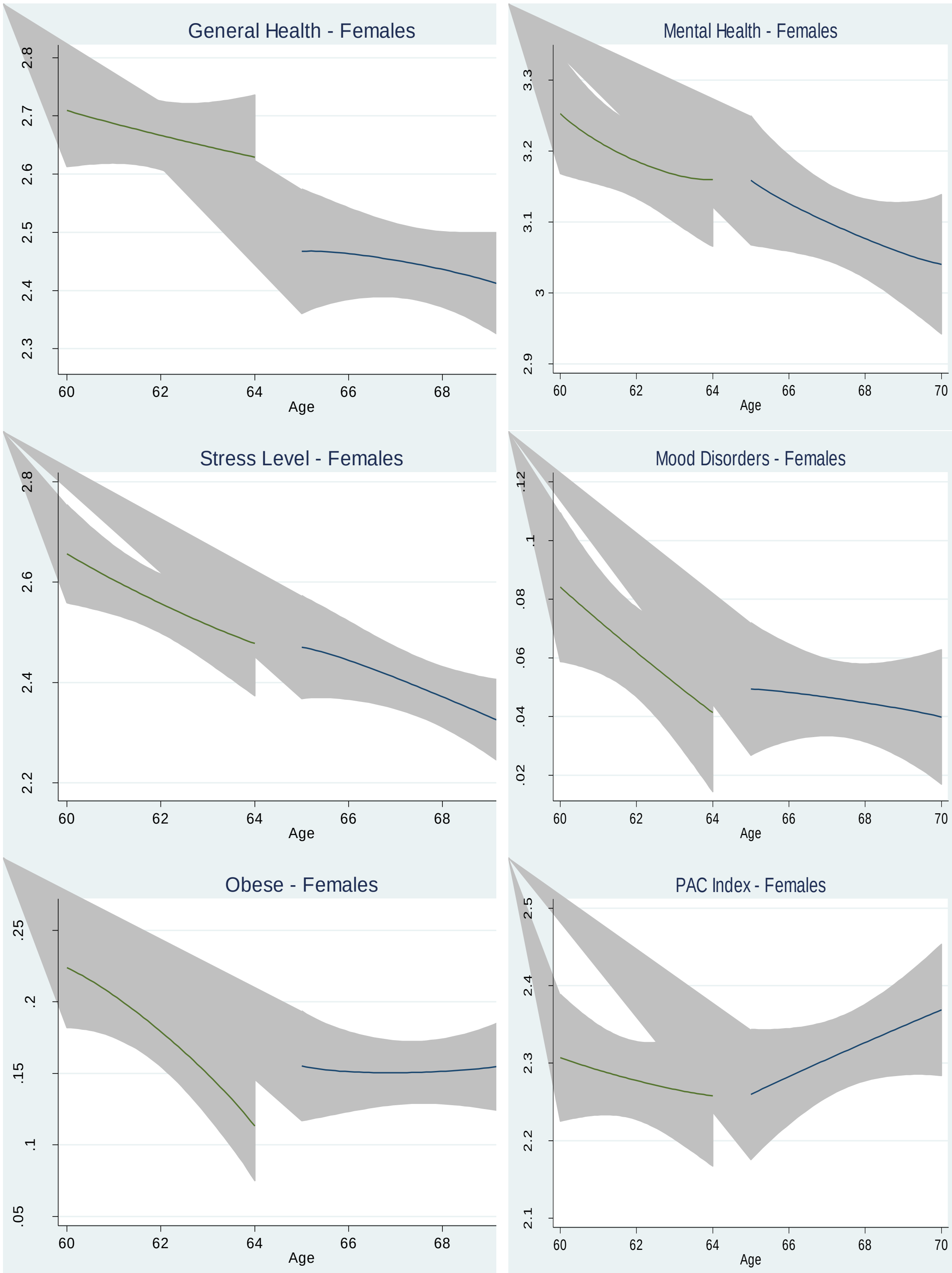


Figure 2.5: Test of the Discontinuity of Covariates at the Cutoff – Full Sample

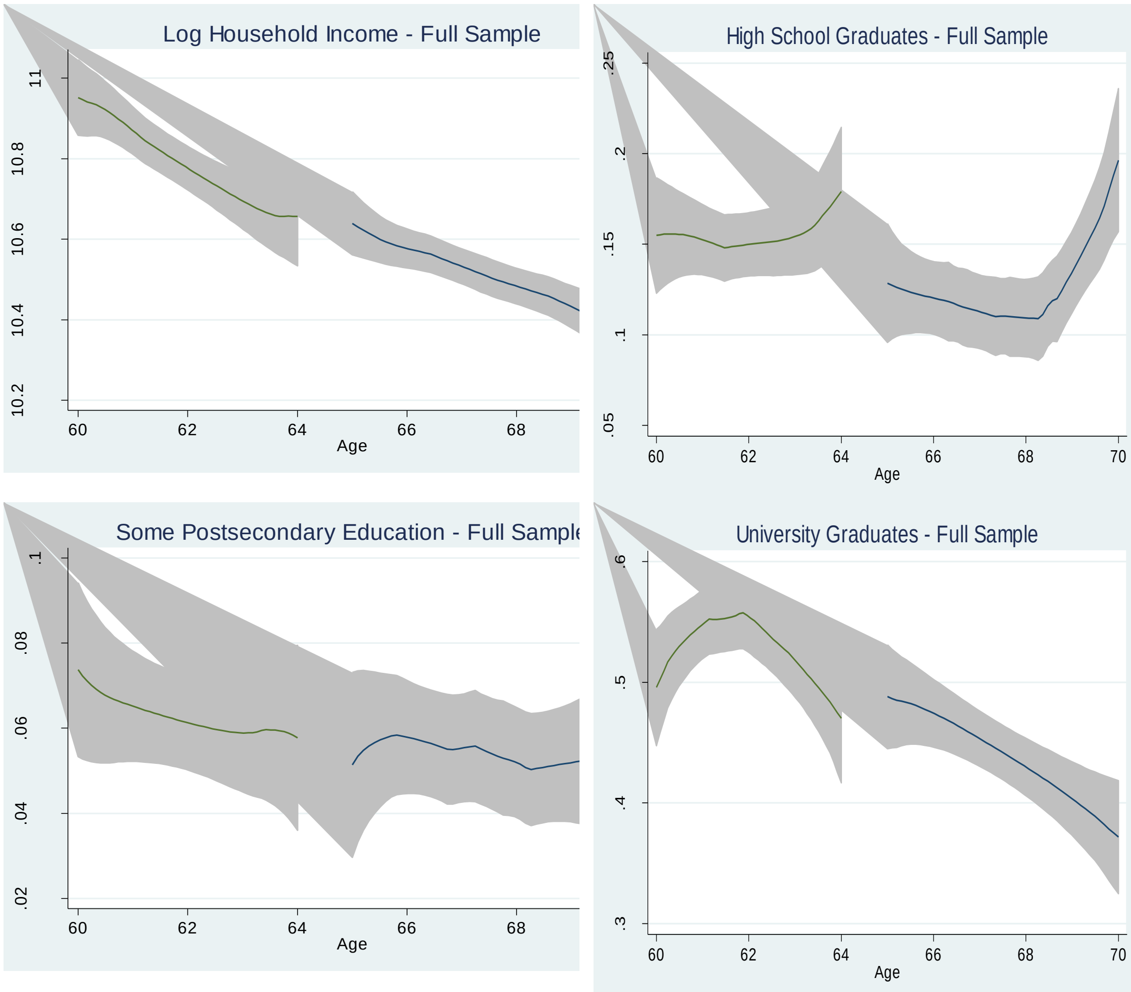


Figure 2.6: Test of the Discontinuity of Covariates at the Cutoff – Male Only

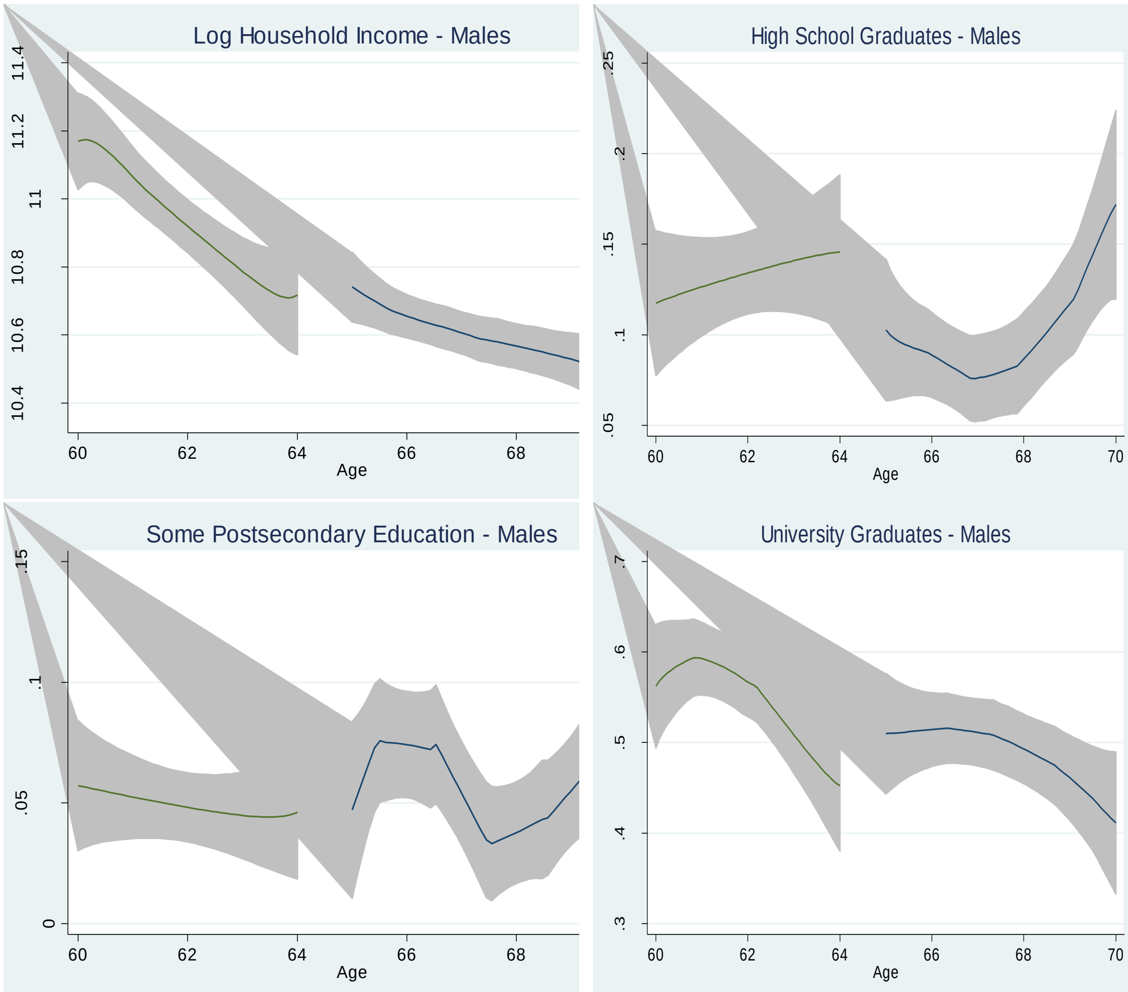
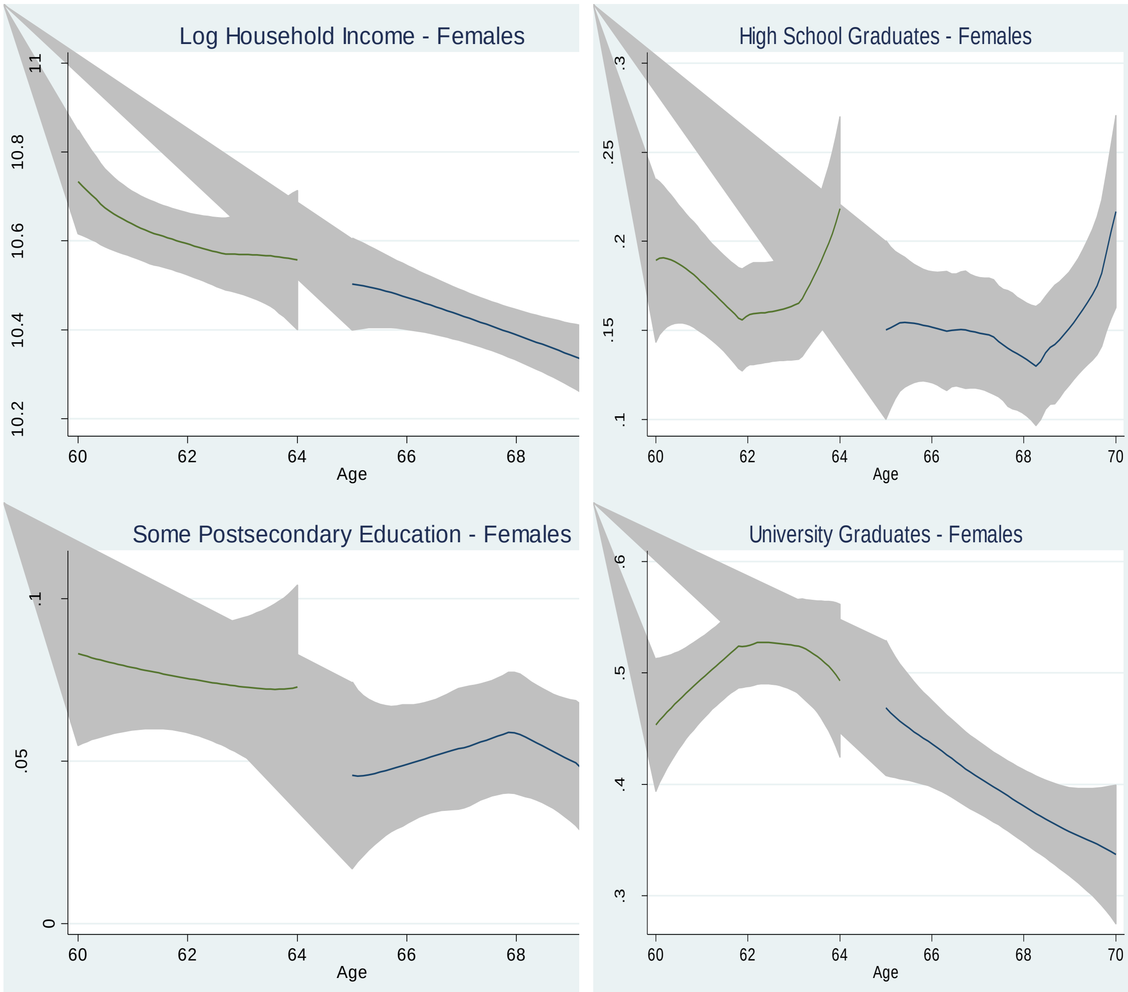


Figure 2.7: Test of the Discontinuity of Covariates at the Cutoff – Female Only



Endnotes

[1] This paper is co-authored with Byron Lee, a PhD candidate at the Center for Industrial Relations and Human Resources, University of Toronto

Reference List

Bound, J., & Waidmann, T. (2007). Estimating the health effects of retirement. Working Paper.

Charles, K. (2004). Is retirement depressing?: Labor force inactivity and psychological well-being in later life. Research in Labor Economics, 23, 269-299.

Coe, N., & Zamarro, G. (2008). Retirement effects on health in Europe. RAND Working Paper no. 588.

Dave, D., Rashad, I., & Spasojecvic, J. (2008). The effects of retirement on physical and mental health outcomes. Southern Economic Journal, 75, 497-523.

Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. Econometrica, 69, 201-209.

Imbens, G., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. Journal of Econometrics, 142(2), 615-635.

Johnston, D., & Lee, W. (2009). Retiring to the good life? The short-term effects of retirement on health. Economics Letters, 103, 8-11.

Lee, D., & Lemieux, T. (2009). Regression discontinuity designs in economics. NBER Working Paper No.14723.

Mein, G., Marikainen, P., Hemingway, H., Stansfeld, S., & Marmot, M. Is retirement good or bad for mental and physical health functioning? Whitehall II longitudinal study of civil servants. Journal of Epidemiology and Community Health, 57, 46-49.

Mojon-Azzi, S., Sousa-Poza, A., & Widmer, R. (2007). The effect of retirement on health: A panel analysis using data from the Swiss household panel. Swiss Medical Weekly, 137, 581-585.

Rohwedder, S., & Willis R. (2010). Mental retirement. Journal of Economic Perspectives, 24(1), 119-138.

Stock, J., & Yogo, M. (2002). Testing for weak instruments in linear IV regression. NBER Technical Working Paper 284.

Toumi, K., Jarvinen, E., Eskelinen, Leena, & Llmarinen, J. (1991). Effect of retirement on health and work ability among municipal employees. Scandinavian Journal of Work, Environment and Health, 17(1), 75-81.

3:
PEER EFFECTS ON OBESITY AMONG ADOLESCENTS

3.1 Introduction

In recent years, obesity has become a major public health concern in the United States. Data from the 1976-1980 and 2003-2006 National Health and Nutrition Examination Survey (NHANES) shows the prevalence of obesity among US children and adolescents has increased dramatically over the last 30 years. The prevalence of obesity among children aged 2 to 5 has increased from 5.0% to 12.4%; for children aged 6 to 11, prevalence of obesity has increased from 6.5% to 17.1%; and for adolescents aged 12 to 19, the prevalence of obesity has increased from 5.0% to 17.6% (Ogden et al., 2002 and 2008). The rise in the prevalence of obesity among US children increases the current burden on the health care system as obese children are at an increased risk for high cholesterol, high blood pressure, type 2 diabetes and heart problems (Freedman et al., 2001; Sinha et al., 2002). In addition, the increasing prevalence of childhood obesity is likely to put even more pressure on the health care system in the future because overweight or obesity in adolescence often persists into adulthood (Whitaker et al., 1997), and overweight and obesity are known risk factors for diabetes, heart disease, high blood cholesterol, and stroke among adults.

Since the social costs of childhood obesity could be substantial, understanding the socioeconomic determinants of childhood obesity is important. There are a number of known factors which contribute to the increase in the prevalence of overweight or obesity among children. First, children become more sedentary nowadays as they turn away from physical activity and spend more time on television, computer and video games. Second, fast food consumption among children has also increased significantly over the past 20 years (Lobstein et al., 2004). Third, the increase in the prevalence of obesity among adults could have an implication on the widespread of obesity among children as children of obese parents are also more likely to become obese as well (Beardslee et al., 1998). However, the effect of social networks, a potential risk factor for overweight and obesity in children, has received very little attention until recently.

Social networks could affect children's weight status in a number of ways. First, children might select friends that share common eating behaviours and tastes. Being friends with obese children might reinforce the negative behaviours that cause obesity. Second, children who are surrounded by obese peers or parents might develop inaccurate perceptions of healthy weight status. They could consider being obese as perfectly normal and as a result would not try to avoid it. Third, children could imitate unhealthy eating habits of their obese peers or parents, and it would certainly increase the risk of being obese among those children.

Empirical studies on the relationship between obesity and social networks are limited because few datasets contain information on the social links between individuals. A study on the relationship between social networks and obesity among adults by Christakis and Fowler (2007) (CF thereafter) shows obesity could spread among families and friends. These authors estimate that a person who has an obese spouse is 37% more likely to become obese a few years later. The estimated impact of obese friends is even larger: a person is 57% to 171% more likely to become obese a few years later if he or she has obese friends. The social network effect does not disappear even if those friends live far apart from the person.

Other studies try to investigate the relationship between obesity and social networks among adolescents. Using data from the National Longitudinal Adolescent Health Survey (Add Health), Halliday and Kwak (2007) find a similar effect of social networks among adolescents as in CF. The effect, however, is sensitive to the definition of the outcome variable. They find an insignificant effect for the change in BMI, but a significant effect for the binary variable of overweight. Therefore, they suggest the results found in CF are not conclusive. On the other hand, Trogdon et al. (2008) show that mean BMI among friends in the Add Health data is positively correlated with an adolescent's own weight. In addition, the probability of an adolescent being overweight is also positively correlated with the proportion of overweight friends. Their results suggest the relationship between obesity and social networks is robust even under various definitions of weight status. One thing that is worth to note is the two papers only look at whether having more overweight friends would increase the likelihood of an adolescent being overweight, but not the likelihood of being obese if the adolescent has more obese friends.

Cohen-Cole and Fletcher (2008) (CCF thereafter) are skeptical about CF results. CCF point out that the CF model suffers from three potential problems: 1) it does not include a rich set of controls for environmental effects; 2) selection bias is not well addressed in the CF model and 3) the CF dynamic model could provide estimates with huge biases. Using the Add Health data and addressing all three potential problems that lie within the CF model, CCF do not find significant peer effects on adolescent weight. They suggest environmental effects are the more likely determinant of adolescent weight rather than peer effects. However, in a follow-up study that uses the same Add Health dataset as in Cohen-Cole and Fletcher (2008), Christakis and Fowler (2008) show peers effects are still significant even after controlling for environmental effects. In the same article, Christakis and Fowler also provide additional evidence to support their claims in their 2007 study.

Two other studies report similar effect of social networks on obesity among children as in Chritakis and Fowler (2008). Maximova et al. (2008) suggest that children surrounded by overweight peers and parents may develop inaccurate perceptions of healthy weight status. Therefore, they are more likely to become overweight compared with children surrounded by normal weight parents and peers. Valente et al. (2009) also find overweight youths are more likely to be friends with obese youths. Those children could face higher risk of becoming obese as being friends with obese children might reinforce the negative behaviours that cause obesity.

According to Manski (1993), the challenge of any empirical work on the effect of social networks is the presence of three effects that could have led to the observed outcome, in this case the weight status of an adolescent. They are endogenous social effects, contextual effects and correlated effects. These three effects have different policy implications, and therefore, researchers want to distinguish these three different effects of social networks on weight status. This paper and all the paper cited above try to estimate the endogenous social effects, that is, whether an adolescent weight status is directly affected by his/her friends' weight status. If the main effects of social networks on weight status among adolescents are endogenous social effects, policy that aims to reduce weight among adolescents will have a larger effect because of the presence of social multiplier. That is, you will lose weight because your friends do.

Some of the papers cited above try to control for the correlated effect by using instrumental variables, which often requires strong assumptions such as exogeneity of the IV. While all the papers cited aim to estimate the endogenous social effects, violation of any of the underlying assumptions in the model results in the estimates presented in those studies being inconsistent. In this paper, a linear regression model is used to estimate endogenous social effects using data from the National Longitudinal Study of Adolescent Health (Add Health). The consistency of estimates depends on the assumption of zero correlation between the main explanatory variable and unobservable factors. While other papers cited have made this assumption, the model used in this paper allows for different degree of correlation between the main explanatory variable and unobservable factors. If the estimate of the main explanatory variable is robust across various degree of correlation between the main explanatory variable and unobservable factors, then the estimate can provide some insight on whether an adolescent's weight status is directly affected by his/her friends' weight status even with the presence of omitted variable bias.

The paper proceeds as follows. Section 2 discusses the dataset and variables used in this study. The linear regression model is described in Section 3. Statistical results are presented in Section 4, and Section 5 concludes.

3.2 Data

We study the effect of school-level social interactions on adolescent weight status using data from the National Longitudinal Study of Adolescent Health (Add Health). Add Health is one of the most comprehensive school-based longitudinal surveys of health-related behaviours of adolescents in grades 7-12 in the United States. The survey was administered by the Carolina Population Center at the University of North Carolina. The complete survey contains a total of three different waves. The first wave was administered in 1994-95. A nationally representative sample of U.S. high schools was randomly selected, and a sample of about 20,000 students from the selected high schools was surveyed. Two follow-up surveys were administered to the same group of students in the second wave (1996) and third wave (2001-2002). The complete survey contains information on schools, families, health-related behaviours of adolescents and socioeconomic characteristics of adolescents. More importantly, the survey provides information on the social ties between individuals at the school level which enables our study of the impact of social networks on adolescent weight status.

In this paper, we use the first wave of Add Health data. Our sample only includes students from grade 10 to 12. Only grade 10 to 12 students are included in the sample because we do not want our estimates to possibly show peer effects from last attended school. Most of the grade 9 students have just moved to a new school by the time of the survey, so the weight status of an adolescent might be a reflection of behaviours of the adolescent’s peer group in the old school other than the new school. Grade 10 to 12 students exhibit less mobility between schools, therefore, any change in the weight status of an adolescent is more likely to be a reflection of behaviours of the adolescent’s peer group in the new school.

The main outcome variables of interest are the BMI of an adolescent, the probability of an adolescent being overweight and the probability of an adolescent being obese. We define the weight status of adolescent using BMI-for-age growth charts provided by the Centers for Disease Control and Prevention (CDC) for both boys and girls. According to the growth charts, an adolescent is categorized as underweight, healthy weight, overweight or obese based on the adolescent's BMI relative to the BMI of children of the same sex and age. Adolescents whose BMI is in the 95th percentile or above among children of the same sex and age are categorized as obese. Adolescents whose BMI is between the 85th and 95th percentile are categorized as overweight. Even though we are using an objective measure to define an adolescent's weight status, our outcome variables are still subject to a certain degree of measurement errors because the BMI of an adolescent is calculated from self-reported, not measured, height and weight. Spencer et al. (2001) compare self-reported and measured height and weight among adults, and they find around 22% of the men and 18% of the women in the sample self-reported their height and weight incorrectly. Results from this study suggest self-reported measures are subject to some measure errors but are still useful for determining a child's weight status.

Other variables that we use in the model include variables that describe the personal and family characteristics of the adolescent, and, more importantly, the characteristics of the adolescent's peer group. Variables that describe the personal characteristics of the adolescents include gender, age, ethnicity, hours spent on watching TV per week, physical activeness and birth weight. A measure of physical activeness of the adolescent is included in the model because it is highly correlated with obesity. Research shows more physical activities would certainly lower the chance of being obese (Hemmingsson and Ekelund 2006). Dietz and Gortmaker (1985) find that more hours of television watching is associated with higher risk of being obese among children. Therefore, number of hours of television watching on average per week is included in the model to control for the possible effects of the activity on obesity. Birth weight of the adolescents is included in the model because infants with high birth weight are also more likely to be overweight or obese during their childhood or adolescence (Persons et al. 2008).

Variables that describe the family characteristics of the adolescent are also used in the model, and they include parental weight status, mother's education level and work status of the mother. Parental weight status is correlated with the weight status of their children as adolescents who have an obese mother or father are also more likely to be obese (Agras et al., 2004). To control for socioeconomic differences among adolescents, the adolescent's gender, race, work status of the mother and dummies for the highest level of education completed by the mother are included. More importantly, we want to identify the role of social networks in the spread of obesity. Therefore, a variable which shows the proportion of obese or overweight peers in an adolescent's peer group is also included in our model. We define the peer group to include all students who are in the same school and same grade with the adolescent because we are particularly interested in measuring school-level effects on the spread of obesity among adolescents. In addition to the characteristics of the adolescent's peer group, dummy variables for school are also included in the model. Our sample contains 2523 observations.

Summary statistics for the main variables used in the model are presented in Table 3.1. The proportion of adolescents who are obese in the sample of 2523 adolescents from grade 10 to 12 is about 14%, and around 33% of the adolescents are overweight (including obese adolescents). About 79% of the adolescents are whites, and around 46% of the adolescents in the sample are males. There are 1139 boys in the male subsample and 1384 girls in the female subsample. The prevalence of obese and overweight is higher among boys. Around 21% of the boys are obese in the male subsample, while only 8% of girls are obese in the female subsample. About 43% of the boys are overweight (including obese) in the male subsample, and about 24% of girls are overweight (including obese) in the female subsample. Average birth weight of the adolescents in the sample is about 6.97 pounds, which is a bit lower than the national average of 7.5 pounds (Centers for Disease Control and Prevention). The average proportion of obese and overweight peers in a peer group is about 13% and 30% respectively, and the numbers are about the same for the male and female subsamples. Boys are more physically active on average compared with girls in the sample. Adolescents in the sample spend about 14 hours watching TV per week on average, and boys spend slightly more hours on TV watching than girls.

Many of the adolescents in the sample have well educated mothers. Around 29% of the mothers have a university or college degree, 24% of the mothers have some postsecondary education, and 33% of the mothers have a high school diploma. There is no major difference in the education level of the mother between the male and female subgroups. About 85% of the mothers have a full time job.

3.3 Methodology

This paper studies endogenous peer effects, that is, whether an adolescent's body weight is affected by the average body weight of his/her peers. According to Manski (1993), the challenge of any empirical work on the effect of social networks is the presence of three effects that could have led to the observed outcome, in this case the weight status of an adolescent. Those three effects are endogenous social effects, contextual effects and correlated effects. These three effects have different policy implications, and therefore, researchers want to distinguish these three different effects of social networks on weight status. Endogenous social effects are the effects that I am trying to estimate, so do all papers cited, in this paper. I want to see whether an adolescent's weight status is directly affected by his/her friends' weight status. If the main effects of social networks on weight status among adolescents are endogenous social effects, policy that aims to reduce weight among adolescents will have a large effect because of the presence of social multiplier. That is, you will lose weight because your friends do. Contextual effects are the effects of peers' characteristics other than weight on an adolescent's own weight. If an adolescent gains weight through only contextual effects, policy that aims to reduce weight among adolescents will have a smaller effect because an adolescent would not lose weight if his/her peers do. The last effects, which are correlated effects, suggest an even smaller role in policy that reduces adolescent obesity because an adolescent's weight and his/her peers' weight are influenced by some unobserved factors that are common to both the adolescent and peers.

The following OLS model estimates the effect of social networks on obesity among adolescents for adolescent i with peer group g in school s:

$$Obesity_{igs} = \beta_0 + \beta_1 Obesity\_Friend_{gs} + \gamma X_i + \rho_s + \tau_g + \varepsilon_i \quad (1)$$

In (1), $Obesity_{igs}$ is a dependent variable that indicates whether the adolescent is obese or not. X_i are controls for personal and family characteristics of the adolescent, $Obesity\_Friend_{gs}$ is the proportion of obese peers within the adolescent's peer group, ρ_s and τ_g are dummies which control for school and grade fixed effects and ε_i is the error term. The same specification is used to estimate the effect of social networks on the probability of being overweight and BMI among adolescents by replacing $Obesity_{igs}$

with a binary variable that indicates whether the adolescent is overweight or not, and with a continuous variable for BMI. β_1 is the main parameter of interest and is supposed to show endogenous social effects, that is, whether an adolescent's weight status is directly affected by his/her friends' weight status. However, estimates of β_1 in the model are likely to be biased (Manski 1993). Biases in β_1 can be caused by sorting which make the estimates from (1) pick up both endogenous social effects and also correlated effects at the same time. Sorting occurs if adolescents are in the same peer group because of some common unobservables among those adolescents within the same group and those unobservables affect the weight status of the adolescent. In our context, if adolescents become friends due to the fact that they all like fast food, then β_1 would also show the effect of fast food consumption on weight status, not just peer effects. Without controlling for sorting, estimates from (1) are likely to be subjected to omitted variable bias.

To overcome this problem, a relative correlation restriction model developed in Krauth (2010) is used. The main difference between the OLS model in (1) and the relative correlation restriction model is the assumption of the correlation between the main explanatory variable and unobservable factors. In the OLS model, we assume zero correlation between the main explanatory variable and unobservable factors. If there actually is zero correlation between the main explanatory variable of interest and unobservable factors, then the estimates of β_1 are consistent in the OLS model since there is no omitted variable bias. However, the validity of this assumption is questionable if sorting presents. On the other hand, the relative correlation restriction model allows for various degree of correlation between the main explanatory variable and unobservable factors. In other words, the relative correlation restriction model allows for various degree of omitted variable bias. I am interested to see if the value of β_1 would fluctuate under various degree of non-zero correlation between the main explanatory variable of interest and unobservable factors. If the value of β_1 is always positive under different sets of correlation restrictions, then we can conclude the sign of endogenous social effects even if omitted variable bias presents. That is, having more obese friends would directly increase, directly decrease or not affect your chance of being obese.

Using the relative correlation restriction model developed in Krauth (2010), equation (1) is re-estimated under the following assumption regarding the correlation between the main explanatory variable of interest and unobservable factors:

$$Corr(Z,\varepsilon) = \lambda_0 Corr(Z,\gamma X) \ for\ some\ \lambda_0 \epsilon \Lambda \tag{2}$$

where Z is the main explanatory variable of interest, which is the average weight characteristic of the peer group, X are other independent variables in the model, and ε is the error term in (1). Since we do not observe $Corr(Z,\varepsilon)$, we assume the correlation between the main explanatory variable and unobservables is proportional to the correlation between the main explanatory variable and observables, which is $Corr(Z,\gamma X)$, by a factor of λ_0. Different values of λ_0 suggest different level of bias in β_1:

1) If λ_0 = 0, then estimates of β_1 are consistent and captures the endogenous social effects.

2) If λ_0 > 0, then $Corr(Z,\varepsilon)$ is of the same sign as $Corr(Z,\gamma X)$. Estimates of β_1 are less biased by controlling for X in the model.

3) If $\lambda_0 < 0$, then $Corr(Z, \varepsilon)$ is of the opposite sign as $Corr(Z, \gamma X)$. Estimates of β_1 could be less biased or more biased by controlling for X in the model.

4) If $\lambda_0 = 1$, then $Corr(Z, \varepsilon)$ is of the same sign and magnitude as $Corr(Z, \gamma X)$. The bias in estimates of β_1 is fully offset by controlling for X in the model.

In addition, the assumption in (2) is slightly modified to (3) below to control for fixed effects:

$$Corr(\hat{Z}, \varepsilon) = \lambda_0 Corr(\hat{Z}, \gamma\hat{X}) \text{ for some } \lambda_0 \epsilon \Lambda \tag{3}$$

where $\hat{\hat{Z}}$ is the residual from a linear regression of Z on the grade and school dummies, and $\hat{X}$ is the residual from a linear regression of X on the grade and school dummies.

Re-estimating equation (1) using different values of λ_0 provides bounds on β_1. If the value of β_1 is always positive under different sets of correlation restrictions, then we can conclude having more obese friends would directly increase your chance of being obese. Other studies cited either assume average peer background characteristics do not directly affect the weight status of the adolescent or they use instrumental variables to solve the omitted variables problem (Halliday and Kwak 2007, Trogdon et al. 2008). However, identification using instrumental variables requires that the IV affects the outcome variable only through an observed characteristic in the model and does not correlate with any unobservable in the data. In our context, the ideal IV should have no direct effect on the weight status of an adolescent but affect the weight status of an adolescent indirectly through its effect on the average weight status of the peer group. This assumption will be violated and the resulting estimates are inconsistent if sorting occurs, e.g. adolescents become friends because they all like fast food. As in all the paper cited above, the model in (1) does not control for contextual effects. Therefore, the estimates would also capture contextual effects if they in fact present.

3.4 Results

3.4.1 OLS Results

OLS estimates of peer effects on BMI, chance of being obese and chance of being overweight are presented in Table 3.2 through 3.4 respectively. Bounds on peer effects on BMI, chance of being obese and chance of being overweight under different sets of correlation restrictions are presented in Table 3.5 through 3.7 respectively. As discussed in section 3, the OLS model tends to provide inconsistent estimates for endogenous social effects if there exists omitted variables bias. Bounds on peer effects presented in Table 3.5 through 3.7 provide confidence intervals of endogenous social effects if there exists different degree of omitted variable bias. If peer effects are always positive under different sets of correlation restrictions, then we can conclude having more obese friends would increase your chance of being obese even if omitted variable bias presents.

The OLS estimates in Table 3.2 through 3.4 suggest the adolescent's own BMI is positively related to average peers' BMI for the female subsample. For each one unit increase in the average peers' BMI would increase the adolescent girl's BMI by 0.12 unit. Peer effects on boys' BMI are positive but insignificant, and the effect is also insignificant among the full sample. In contrast, having more overweight friends reduces the probability of the adolescent being overweight for the male subsample. For each one percentage point increase in the proportion of overweight friends in the peer group would decrease the chance of the adolescent being overweight by 0.01 percentage point. Peer effects on the chance of the adolescent being obese are positive but insignificant.

Compared with effects on the adolescent's own weight of other variables in the model, peer effects on adolescent weight status are quite small.

White adolescents have a lower chance of being obese. Being a white adolescent decreases the chance of being obese by 7 percentage points compared with non-white adolescent. Male adolescent are more likely to be obese. The chance of being obese is 12 percentage points higher among boys compared with girls, holding everything else constant. Interestingly, adolescents who are more active in sports do not have a significantly lower chance of being obese or overweight. In addition, adolescents who watch TV more often also do not have a significantly higher chance of being obese or overweight. On the other hand, parental characteristics seem to be a more significant determinant of adolescent weight status. Adolescents who have an obese mother or father are more likely to be obese. For the full sample, having an obese mother would increase the chance of the adolescent being obese by 9 percentage points, and having an obese father would increase the chance by 17 percentage points.

For the male subsample, the only significant peer effects on boys' weight status are peer effects on boys' chance of being overweight. Having more overweight friends reduces the probability of the adolescent being overweight for the male subsample. For each one percentage point increase in the proportion of overweight friends in the peer group would decrease the chance of the adolescent being overweight by 0.01 percentage point. Effects of parental characteristics on boys' weight status are stronger. Having an obese mother or father increases the probability of the adolescent being obese as well as being overweight. Having an obese mother would increase the chance of the boy being obese or overweight by 14 and 16 percentage points respectively. Having an obese father would increase the chance of the boy being obese or overweight by 19 or 18 percentage points respectively. Parental characteristics have a larger effect on boys compared with girls. The effect of having an obese mother on the chance of being obese or overweight is insignificant among girls, but the effect is significant and several times bigger among boys.

For the female subsample, girl's own BMI is positively related to average peers' BMI. For each one unit increase in the average peers' BMI would increase the girl's BMI by 0.12 unit. Having more overweight or obese friends would also increase the chance of the female adolescent being overweight or obese, but the effect is not statistically significant. White adolescent girls are less likely to be obese or overweight. Adolescent girls with a higher birth weight have a higher chance of being overweight. Mother education level is positively associated with the adolescent girl's chance of being obese. Having an obese mother or father is positively associated with the probability of the adolescent girl being obese or overweight.

Interestingly, we do not find any effect of sports on adolescent weight status in all of the specifications. And among all our samples, effects of parents' weight status on adolescent weight status are mostly significant, and peer effects on adolescent weight status are sometime significant. It shows the effect of social networks exists, whether it is between families or friends, but the OLS model does not control for sorting and thus is likely to give inconsistent estimates on endogenous social effects. Bounds on peer effects presented in Table 3.5 through 3.7 provide confidence intervals of endogenous social effects if there exists different degree of omitted variable bias.

3.4.2 Relative Correlation Restriction Results

Table 3.5 through 3.7 present peer effects under different degree of relative correlation restrictions. Estimates of peer effects are presented in square brackets, and the 95% asymptotic confidence intervals for peer effects are presented in round brackets. All the confidence intervals are Imbens-Manski (2004) confidence intervals. Results from Table 3.5 through 3.7 suggest OLS estimates are quite robust. The sign of estimated peer effects are mostly positive for all the samples if the correlation between the main explanatory variable and unobservables is below three times the correlation between the main explanatory variable and other controls. However, the estimates turn to negative if there is a high correlation between the main explanatory variable and unobservables. The sign of estimated peer effects would turn into negative if the correlation between the main explanatory variable and unobservable factors is as much as three times the correlation between the main explanatory variable and other controls. One of the possible candidates that creates omitted variable bias in the model is sorting. If the correlation between sorting and weight status of friends is three times the correlation between weight status of friends and other controls such as weight status of parents, then the sign of the estimates would change from positive to negative. However, there is no way to test the true magnitude of omitted variable bias that exists in the model. Given the results, OLS estimates do provide some information on the direction of peer effects on adolescent weight status if omitted variable bias is moderate. There is a need for latter paper which studies peer effects on adolescent weight status to properly control for omitted variable bias such as sorting. Although some of the work cited in this paper use IV to control for omitted variable bias, the use of IV requires strong assumptions such as exogeneity of the IV. Violations of these assumptions would render the IV estimates inconsistent.

3.5 Conclusion

This paper uses a linear regression model to study peer effects on adolescent weight status using data from Add Health. OLS estimates suggest the adolescent's own BMI is positively related to average peers' BMI for the female subsample. For each one unit increase in the average peers' BMI would increase the adolescent girl's BMI by 0.12 unit. Peer effects on boys' BMI are positive but insignificant, and the effect is also insignificant among the full sample. Peer effects on the chance of the adolescent being obese are positive but insignificant. In contrast, having more overweight friends reduces the probability of the adolescent being overweight for the male subsample. For each one percentage point increase in the proportion of overweight friends in the peer group would decrease the chance of the adolescent being overweight by 0.01 percentage point. The result is surprising since we expect both having more obese or overweight friends would increase the adolescent's own probability of being obese or overweight. Such a surprising result could be due to the presence of omitted variable bias; therefore, the model is re-estimated under different degree of correlation between the main explanatory variable and unobservable factors using the relative correlation restriction method developed in Krauth (2010). Estimates under different relative correlation restrictions suggest OLS estimates are still quite robust when omitted variable bias exists. The sign of estimated peer effects would only change if the correlation between the main explanatory variable and unobservable factors is as much as three times the correlation between the main explanatory variable and other controls. One of the possible candidates that creates omitted variable bias in the model is sorting. If the correlation between sorting and weight status of friends is three times the correlation between weight status of friends and other controls such as weight status of parents, then the sign of the estimates would change from positive to negative. However, there is no way to test the true magnitude of omitted variable bias that exists in the model. Given the results, OLS estimates do provide some information on the direction of peer effects on adolescent weight status if omitted variable bias is moderate. There is a need for latter paper which studies peer effects on adolescent weight status to properly control for omitted variable bias such as sorting. Although some of the work cited in this paper use IV to control for omitted variable bias, the use of IV requires strong assumptions such as exogeneity of the IV. Violations of these assumptions would render the IV estimates inconsistent.

Table 3.1: Descriptive statistics of the main variables in the model

	All Adolescents	Male Only	Female Only
BMI	23.22	24.04	22.52
	(5.02)	(5.33)	(4.64)
Overweight	0.33	0.43	0.24
	(0.47)	(0.49)	(0.43)
Obese	0.14	0.21	0.08
	(0.35)	(0.41)	(0.28)
Age	16.13	16.20	16.07
	(0.93)	(0.95)	(0.92)
Child is a male	0.46		
	(0.50)		
Child is white	0.79	0.82	0.76
	(0.41)	(0.38)	(0.43)
Birth weight (pounds)	6.97	7.20	6.77
	(1.33)	(1.34)	(1.29)
Hours of TV per week on average	14.31	15.36	13.43
	(13.18)	(13.65)	(12.71)
Average BMI of peers	22.81	22.91	22.74
	(3.79)	(3.65)	(3.91)
Proportion of obese peers	0.13	0.12	0.13
	(0.27)	(0.27)	(0.27)
Proportion of overweight peers	0.30	0.30	0.30
	(0.36)	(0.37)	(0.36)
Physical activities indicator	0.69	0.81	0.59
	(0.46)	(0.38)	(0.49)
Mother has a university degree	0.29	0.30	0.29
	(0.46)	(0.46)	(0.45)
Mother has some post-secondary education	0.24	0.25	0.24
	(0.43)	(0.43)	(0.43)
Mother is a high school graduate	0.33	0.32	0.34
	(0.47)	(0.47)	(0.47)
Mother has a full time job	0.85	0.87	0.84
	(0.35)	(0.34)	(0.37)
Mother is obese	0.18	0.20	0.17
	(0.39)	(0.40)	(0.37)
Father is obese	0.12	0.12	0.11
	(0.32)	(0.33)	(0.31)
Observations	2523	1139	1384

Standard deviations are in brackets.
All descriptive statistics are weighted using survey weights.

Table 3.2: OLS estimates of peer effects on BMI

	All Adolescents	Male Only	Female Only
Average BMI of peers	0.11	0.08	0.12**
	(0.07)	(0.05)	(0.05)
Mother has a university degree	-0.40	-0.49	-0.42
	(0.46)	(0.77)	(0.53)
Mother has some post-secondary education	-0.52	-1.56*	0.14
	(0.47)	(0.79)	(0.54)
Mother is a high school graduate	0.00	-0.76	0.88*
	(0.48)	(0.82)	(0.52)
Mother has a full time job	-0.34	-0.78	0.16
	(0.41)	(0.71)	(0.42)
Mother is obese	1.52***	2.28***	0.92*
	(0.42)	(0.60)	(0.51)
Father is obese	2.40***	2.46***	2.26***
	(0.59)	(0.85)	(0.68)
Birth weight	0.20*	0.01	0.42***
	(0.10)	(0.16)	(0.14)
Hours of TV per week on average	0.02*	0.02	0.02
	(0.01)	(0.02)	(0.01)
Physical Activity Indicator	0.25	0.43	0.11
	(0.29)	(0.50)	(0.34)
Child's age	0.17	0.13	0.16
	(0.26)	(0.37)	(0.33)
Child is male	1.43***		
	(0.28)		
Child is white	-1.91***	-1.29*	-2.24***
	(0.41)	(0.68)	(0.55)
Constant	15.15***	18.92***	16.62***
	(3.41)	(3.96)	(4.70)
Observations	2523	1139	1384
R^2	0.15	0.19	0.21

Note: Other control variables included are: grade and school fixed effects.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are cluster-robust and are in brackets.
All regressions are weighted using survey weights.

Table 3.3: OLS estimates of peer effects on obesity

	All Adolescents	Male Only	Female Only
Proportion of obese peers	0.06	0.07	0.05
	(0.04)	(0.05)	(0.04)
Mother has a university degree	-0.01	-0.02	-0.01
	(0.03)	(0.06)	(0.02)
Mother has some post-secondary education	0.03	-0.01	0.05*
	(0.03)	(0.06)	(0.03)
Mother is a high school graduate	0.02	0.00	0.06**
	(0.03)	(0.06)	(0.03)
Mother has a full time job	0.03	0.05	0.03
	(0.02)	(0.05)	(0.02)
Mother is obese	0.08***	0.14***	0.05
	(0.03)	(0.05)	(0.04)
Father is obese	0.16***	0.19***	0.13***
	(0.04)	(0.07)	(0.05)
Birth weight	0.01	-0.00	0.01
	(0.01)	(0.01)	(0.01)
Hours of TV per week on average	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Physical Activity Indicator	0.02	0.03	0.01
	(0.02)	(0.04)	(0.02)
Child's age	-0.02	-0.04	-0.01
	(0.02)	(0.03	(0.02)
Child is male	0.12***		
	(0.02)		
Child is white	-0.07**	-0.05	-0.10***
	(0.03)	(0.05)	(0.13)
Constant	0.12	0.26	0.11
	(0.18)	(0.31)	(0.20)
Observations	2523	1139	1384
R^2	0.13	0.18	0.16

Note: Other control variables included are: grade and school fixed effects.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are cluster-robust and are in brackets.
All regressions are weighted using survey weights.

Table 3.4: OLS estimates of peer effects on overweight

	All Adolescents	Male Only	Female Only
Proportion of overweight peers	0.04	-0.01*	0.06
	(0.04)	(0.00)	(0.05)
Mother has a university degree	-0.06	0.02	-0.14**
	(0.05)	(0.07)	(0.06)
Mother has some post-secondary education	-0.05	-0.05	-0.06
	(0.05)	(0.07)	(0.06)
Mother is a high school graduate	-0.01	0.01	-0.02
	(0.04)	(0.06)	(0.06)
Mother has a full time job	-0.01	-0.07	0.04
	(0.04)	(0.06)	(0.04)
Mother is obese	0.09**	0.16***	0.04
	(0.04)	(0.06)	(0.05)
Father is obese	0.17***	0.18***	0.16***
	(0.05)	(0.08)	(0.06)
Birth weight	0.01	-0.00	0.02*
	(0.01)	(0.02)	(0.01)
Hours of TV per week on average	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)
Physical Activity Indicator	0.02	0.05	0.01
	(0.02)	(0.05)	(0.03)
Child’s age	-0.02	-0.02	-0.03
	(0.02)	(0.04)	(0.03)
Child is male	0.19***		
	(0.03)		
Child is white	-0.13***	-0.07	-0.13**
	(0.04)	(0.07)	(0.06)
Constant	0.34	0.49	0.72
	(0.35)	(0.38)	(0.53)
Observations	2523	1139	1384
R^2	0.13	0.18	0.14

Note: Other control variables included are: grade and school fixed effects.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Standard deviations are cluster-robust and are in brackets.
All regressions are weighted using survey weights.

Table 3.5: Bounds on peer effect on child's BMI

Relative Correlation Restriction (Λ)	All Adolescents	Male Only	Female Only
[0.00]	[0.11]	[0.08]	[0.12]
	(0.06,0.17)	(-0.01,0.16)	(0.06,0.18)
[0.00,0.25]	[0.08,0.11]	[0.06,0.08]	[0.1,0.12]
	(0.03,0.17)	(-0.03,0.16)	(0.04,0.18)
[0.00,0.50]	[0.06,0.11]	[0.03,0.08]	[0.08,0.12]
	(0.00,0.17)	(-0.06,0.16)	(0.02,0.18)
[0.00,0.75]	[0.03,0.11]	[0.01,0.08]	[0.05,0.12]
	(-0.03,0.17)	(-0.09,0.16)	(-0.01,0.18)
[0.00,1.00]	[0.00,0.11]	[-0.01,0.08]	[0.03,0.12]
	(-0.06,0.17)	(-0.12,0.16)	(-0.04,0.18)
[0.00,3.00]	[-0.26,0.11]	[-0.24,0.08]	[-0.20,0.12]
	(-0.43,0.17)	(-0.37,0.16)	(-0.37,0.18)
[0.00,5.00]	[-0.66,0.11]	[-0.58,0.08]	[-0.53,0.12]
	(-1.10,0.17)	(-1.18,0.16)	(-0.97,0.18)
[0.00,10.00]	(-∞,∞)	(-∞,∞)	(-∞,∞)
	(-∞,∞)	(-∞,∞)	(-∞,∞)
[0.00,∞)	(-∞,∞)	(-∞,∞)	(-∞,∞)
	(-∞,∞)	(-∞,∞)	(-∞,∞)
(-∞,0.00]	[-0.11,0.70]	[0.08,1.19]	[0.12,1.51]
	(0.06,∞)	(-0.01,∞)	(0.06,∞)

Note: All regressions are weighted using survey weights.
Relative correlation restrictions are in the first column. Intervals in square brackets are the bounds, and intervals in the round brackets are 95% cluster-robust asymptotic confidence intervals.

Table 3.6: Bounds on peer effect on child's probability of being obese

Relative Correlation Restriction (Λ)	All Adolescents	Male Only	Female Only
[0.00]	[0.06]	[0.07]	[0.05]
	(0.02,0.11)	(0.00,0.13)	(0.00,0.10)
[0.00,0.25]	[0.06,0.06]	[0.06,0.07]	[0.05,0.05]
	(0.01,0.11)	(-0.00,0.13)	(-0.00,0.10)
[0.00,0.50]	[0.05,0.06]	[0.05,0.07]	[0.04,0.05]
	(0.00,0.11)	(-0.02,0.13)	(-0.00,0.10)
[0.00,0.75]	[0.04,0.06]	[0.04,0.07]	[0.04,0.05]
	(-0.01,0.11)	(-0.03,0.13)	(-0.01,0.10)
[0.00,1.00]	[0.03,0.06]	[0.03,0.07]	[0.04,0.05]
	(-0.03,0.11)	(-0.05,0.13)	(-0.02,0.10)
[0.00,3.00]	[-0.06,0.06]	[-0.06,0.07]	[0.01,0.05]
	(-0.19,0.11)	(-0.29,0.13)	(-0.12,0.10)
[0.00,5.00]	[-0.14,0.06]	[0.17,0.07]	[-0.02,0.05]
	(-1.04,0.11)	(-0.61,0.13)	(-0.24,0.10)
[0.00,10.00]	[-0.41,0.06]	(-∞,∞)	[-0.10,0.05]
	(-1.04,0.11)	(-∞,∞)	(-0.59,0.10)
[0.00,∞)	(-∞,∞)	(-∞,∞)	(-∞,∞)
	(-∞,∞)	(-∞,∞)	(-∞,∞)
(-∞,0.00]	[0.06,2.23]	[0.07,0.77]	[0.05,1.03]
	(0.02,∞)	(0.00,∞)	(0.00,∞)

Note: All regressions are weighted using survey weights.
Relative correlation restrictions are in the first column. Intervals in square brackets are the bounds, and intervals in the round brackets are 95% cluster-robust asymptotic confidence intervals.

Table 3.7: Bounds on peer effect on child's probability of being overweight

Relative Correlation Restriction (Λ)	All Adolescents	Male Only	Female Only
[0.00]	[0.04]	[-0.01]	[0.06]
	(-0.01,0.08)	(-0.08,0.07)	(0.01,0.11)
[0.00,0.25]	[0.03,0.04]	[-0.02,-0.01]	[0.05,0.06]
	(-0.02,0.08)	(-0.10,0.07)	(-0.00,0.11)
[0.00,0.50]	[0.02,0.04]	[-0.03,-0.01]	[0.04,0.06]
	(-0.04,0.08)	(-0.12,0.07)	(-0.02,0.11)
[0.00,0.75]	[-0.00,0.04]	[-0.04,-0.01]	[0.02,0.06]
	(-0.08,0.08)	(-0.15,0.07)	(-0.03,0.11)
[0.00,1.00]	[-0.03,0.04]	[-0.05,-0.01]	[0.01,0.06]
	(-0.09,0.08)	(-0.17,0.07)	(-0.05,0.11)
[0.00,3.00]	[-0.18,0.04]	[-0.17,-0.01]	[-0.09,0.06]
	(-0.31,0.08)	(-0.44,0.07)	(-0.24,0.11)
[0.00,5.00]	[-0.35,0.04]	[-0.33,-0.01]	[-0.20,0.06]
	(-0.60,0.08)	(-0.84,0.07)	(-0.48,0.11)
[0.00,10.00]	[-1.07,0.04]	(-∞,∞)	[-0.59,0.06]
	(-2.35,0.08)	(-∞,∞)	(-1.55,0.11)
[0.00,∞)	(-∞,∞)	(-∞,∞)	(-∞,∞)
	(-∞,∞)	(-∞,∞)	(-∞,∞)
(-∞,0.00]	[0.04,2.60]	[-0.01,0.68]	[0.06,1.61]
	(-0.01,∞)	(-0.08,∞)	(0.01,∞)

Note: All regressions are weighted using survey weights.
Relative correlation restrictions are in the first column. Intervals in square brackets are the bounds, and intervals in the round brackets are 95% cluster-robust asymptotic confidence intervals.

Reference List

Altonji, J.G., Elder, T.E., & Taber, C.R. (2005). Selection on observed and unobeserved variables: Assessing the effectiveness of catholic schools. Journal of Political Economy, 113(1), 151-184.

Argas,W.S., Hammer, L.D., McNicholas, F., & Kraemer, H.C. (2004). Risk factors for childhood overweight: A prospective study from birth to 9.5 years. Journal of Pediatrics, 145, 20-25.

Beardslee, W.R., Swatling, S., Hoke, L., Rothberg, P.C., Van de Velde, P., Focht, L., & Podorefsky, D. (1998). From cognitive information to shared meaning: Healing principles in prevention intervention. Physchiatry, 61(2), 112-130.

Centers for Disease Control and Prevention. (n.d.). Retrieved from http://www.cdc.gov/nchs/fastats/birthwt.htm

Centers for Disease Control and Prevention Growth Charts. (n.d.). Retrieved from http://www.cdc.gov/growthcharts/cdc_charts.htm

Christakis, N.A., & Fowler, J.H. (2007). The spread of obesity in a large social network over 32 years. New England Journal of Medicine, 357, 370-379.

Christakis, N.A., & Fowler, J.H. (2008). Estimating peer effects on health in social networks. Journal of Health Economics, 27(5), 1400-1405.

Cohen-Cole, E., & Fletcher, J.M. (2008). Is obesity contagious? Social networks vs. environmental factors in the obesity epidemic. Journal of Health Economics, 27(5), 1382-1387.

Dietz, W.H., & Gortmaker, S.L. (1985). Do we fatten our children at the television set? Obesity and television viewing in children and adolescents. Pediatrics, 75, 807-812.

Freedman, D.S., Khan, L.K., Dietz, W.H., Srinivasan, S.R., & Berenson, G.S. (2001). Relationship of childhood obesity to coronary heart disease risk factors in adulthood: the Bogalusa heart study. Pediatrics, 108, 712-718.

Halliday, T.J., & Kwak, S. (2007). Identifying endogenous peer effects in the spread of obesity. Working Paper.

Hemmingsson, E., & Ekelund, U. (2007). Is the association between physical activity and body mass index obesity dependent?. International Journal of Obesity, 31, 663-668.

Imbens, G.W. & Manski, C.F. (2004). Confidence intervals for partially identified parameters. Econometrica, 72, 1845-1857.

Krauth, B.V. (2010). Bounding a linear causal effect using relative correlation restrictions. Working paper.

Lobstein, T., Baur, L., & Uauy, R. (2004). Obesity in children and young people: A crisis in public health. Obesity Reviews, 5(Suppl. 1), 4-85.

Manski, C.F. (1993). Identification of endogenous social effects: The reflection problem. Review of Economic Studies, 60(3), 531-542.

Maximova, K., et al. (2008). Do you see what I see? Weight status misperception and exposure to obesity among children and adolescents. International Journal of Obesity, 32, 1008-1015.

Ogden, C.L., , Johnson, C.L. (2002). Prevalence and trends in overweight among U.S. children and adolescents, 1999–2000. Journal of the American Medical Association, 288, 1728–1732.

Ogden, C.L., Carroll, M.D., & Flegal, K.M. (2008). High body mass index for age among US children and adolescents, 2003–2006. Journal of the American Medical Association, 299, 2401–2405.

Persons, R.K., Sevdy, T.L., & Nichols, W. (2008). Does birth weight predict childhood obesity? Journal of Family Practice, 57(6), 409-410.

Sinha, R., et al. (2002). Prevalence of impaired glucose tolerance among children and adolescents with marked obesity. New England Journal of Medicine, 346, 802-810.

Spencer, E.A., Appleby, P.N., Davey, G.K. & Key, T.J. (2001) Validity of self-reported height and weight in 4808 EPIC-Oxford participants. Public Health Nutrition, 5(4), 561-565.

Trogdon, J.G., Nonnemaker, J., & Pais, J. (2008). Peer effects in adolescent weight. Journal of Health Economics, 27(5), 1388-1399.

Valente, T.W., Fujimoto, K., Chou, C.P., & Sprujit-Metz, D. (2009). Adolescent affiliations and adiposity: A social network analysis of friendships and obesity. Journal of Adolescent Health, 45(2), 2002-204.

Whitaker, R.C., et al. (1997). Predicting obesity in young adulthood from childhood and parental obesity. New England Journal of Medicine, 337(13), 869-873.