Does School Starting Age Matter? The Impact of School on Childhood Obesity, Diet and Time Use in Australia

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Abstract

Consistent with the global obesity epidemic, Australia's rate of childhood obesity has shown an alarming upward trend. While a trend of this magnitude can only be explained by the environment, the exact mechanism remains unclear. Children spend about the same amount of time at home and in school, and therefore it may seem that the school environment is not responsible for childhood obesity. However, this paper reveals that the school environment is responsible for the phenomenon, and that the environment contributes mostly by exposing children to sugar-sweetened beverages, rather than by causing a lack of physical exercise. To establish this claim, this paper compares children who enter school early to children who enter school late, and finds large differences. In the presence of selection, early and late entrants may differ in their individual characteristics, and therefore a direct comparison of the two groups would not be appropriate. To address this identification issue, I implement a fuzzy regression discontinuity (RD) design, in which I exploit the continuity in these individual characteristics around the age cutoff for school entry. This design guarantees a fair comparison between the home and school environments' contributions to childhood obesity. I apply this design to data from the Longitudinal Study of Australian Children (LSAC). My analysis reveals significant differences across the two groups. Early entrants are at least 26% more likely to be obese, and 22% more likely to have a waist-to-height ratio exceeding 0.5 (an indicator for central adiposity). Early entrants are 19% more likely to be exposed to sugar-sweetened beverages. The two groups show no significant difference in exercise time, since exercise time with parents is largely substituted with that in school. This Australian case is of particular interest because the LSAC contains rich information on diet and time use, enabling this design to identify the exact channel behind child obesity in the school environment. This analysis complements the previous studies on childhood obesity.

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1 Introduction

Childhood obesity rates are generally rising in many countries, a phenomenon known as the *obesity epidemic*. In Australia, one in five children are now considered to be overweight or obese by the age of five.[1] The large change in the obesity rates over time has drawn the attention of researchers in multiple fields (Cawley, 2010) due to its negative consequences for health, academic, and economic outcomes in adulthood.[2]

This dramatic increase in childhood obesity rates, which took place within a window of just a few decades, is unlikely to be due to genetic changes across cohorts. It is logical for health economists and researchers to turn to environmental changes, particularly exercise and diet, to explain childhood obesity. Concerning exercise, Cawley et al. (2007, 2013) find that physical education has some impact on childhood and teenage obesity. Concerning diet, Schanzenbach (2009) finds that regularly eating school lunch increases obesity rates by 2%, and Anderson and Butcher (2006) concludes that increasing children's exposure to junk food at school by 10% leads to a 1% increase in average body mass index (BMI). As Anderson et al. (2011) points out, these studies are mostly across-school comparisons, and most of them conclude that a weight-worsening school environment increases the likelihood of childhood obesity.

Although they are significant, these figures are an order of magnitude smaller relative to the overall increase in childhood obesity. One possible reason for this is that diet and exercise time may not have much cross-sectional variation across schools. This is especially true in the case of the United States, whose National School Lunch Program guarantees that the school lunches meet particular standards. In Australia, school lunches and physical exercise are not under centralized management. However, guidelines issued by the government do require that food items provided in school canteens do

[1]See also Ogden et al. (2002). In the United States, reports indicate that the prevalence of obesity quadrupled between 1965 and 2000.

[2]Previous research has revealed the association between childhood obesity and health problems such as type 2 diabetes. Educators find that obese children generally have worse academic outcomes than children with a healthy weight (Taras and Potts-Datema, 2005). As childhood obesity usually persists into adulthood, it may also be a leading cause of adult obesity and its associated economic outcomes, such as decreased earnings (Cawley, 2004).

not differ by a large degree in terms of nutritional values across schools. Therefore, all Australian children have rather homogeneous school environments. This explains the relatively small effects found in the literature.

This paper adopts another identification strategy to complement the literature discussed above. Instead of comparing across schools, this paper compares children who have had earlier exposure to the school environment ("early entrants" hereafter) against their counterparts who have had later exposure ("late entrants" hereafter). This identification strategy of contrasting the school versus the home environment can examine whether the school environment is responsible for childhood obesity in Australia. In school, children experience an environment with regulated exercise and diet. In principle, one might expect that children in school should be less prone to childhood obesity than children at home. However, this paper's findings are the opposite: Children in school have a one-fourth higher probability of being obese than children at home. This figure is significant enough to explain the childhood obesity trend.

A caveat: A direct comparison as it is would be unwarranted. Due to selection, early entrants may differ ex-ante from late entrants. In the language of treatment effects, the two groups differ in their pre-treatment characteristics. As the treatment of concern, the school environment may not cause the difference in obesity rates between the early entrants and the late entrants, even if there is a difference in obesity between the two groups. To achieve a fair comparison, I use a RD design to construct valid comparison groups. Specifically, this paper compares children who are just eligible for school versus children who are just ineligible for school, as determined by an age cutoff. The two groups are thus very close in age, and therefore very close in their pre-treatment characteristics as well. As children may not comply perfectly to the eligibility rule, my design belongs to the class of fuzzy RD that largely resembles an instrumental variable setting (Angrist and Lavy, 1999). Methodologically, this paper is most similar to Anderson et al. (2011) in the sense that these researchers also use age cutoff rules for school attendance to study the effect of school on BMI in the United States.

This paper uses data from the LSAC, which contains rich information on Australian children, including those who attend school and those who do not. In particular, the LSAC contains children's time-use diaries and information regarding food exposure. With these data, I am able to present a more complete analysis that links school attendance, exercise and diet, and ultimately childhood obesity. Analyses that include all of these variables are not available in the previous literature. The LSAC also contains alternative weight outcome measures to offer a broader picture of health. As discussed in Cawley et al. (2013), BMI itself does not capture all potential weight problems. Measures such as waist-to-height ratio can be an even better indicator of problems with overweightness or high fat accumulation. This paper's results include both BMI and alternative measures.

My results reveal that children who enter school early are at least 26% more likely to be obese, and 22% more likely to have a waist-to-height ratio exceeding 0.5, which is a benchmark for central obesity problems. This is largely due to increased exposure to sugar-sweetened beverages at school, as early entrants are 19% more likely to be exposed to them. Time use analysis shows no significant difference between early and late entrants, as active time in school substitutes active time with parents.

In sum, the analysis supports the following story on the cause of childhood obesity: Going to school earlier shifts a large part of the children's time with parents to time in school, especially on weekdays. In addition, schools usually offer different food options than those available at home, which affects children's diet patterns and junk food consumption. Children in school have a substantially larger intake of sugary drinks, whereas their intake of fat and their total time for physical exercise does not differ from children at home.

Using a similar strategy, Anderson et al. (2011) analyze the case in the United States, and find no significant impact of school on childhood obesity. The United States data do not have information on time use and diet; therefore, the exact channel of how school attendance affects obesity rates of children cannot be studied. It is thus unclear whether school and home differ in these two aspects, or if their effects offset each other, resulting in no significant change in childhood obesity. In contrast, the rich data of the LSAC allow this paper to identify the exact mechanism of childhood obesity, adding to the earlier literature on this important social issue.

Studying obesity pertains to the ongoing debate about the setting of school entry age rules, which vary across countries.[3] In Australia, different states and territories have varying age cutoffs for school entry. The Ministerial Council of Education, Employment, Training and Youth Affairs made suggestions for a uniform school entry age ranging from four years five months to four years eight months (Solutions, 2006; Edwards et al., 2011). This would generally make children eligible for school at a younger age than now. More recently, the Australian Primary Principals' Association proposed a higher standard age of five and a half years. While Suziedelyte and Zhu (2015) conclude that an early school start improves Australian children's cognitive skills and negatively affects non-cognitive skills, its effect on children's physical health has not yet been studied.

The rest of this paper is organized as follows. Section 2 reviews the literature on child obesity, with a focus on the school environment. Section 3 provides a summary of the Australian education system, and the state-specific age cutoff rules for school entry. Section 4 describes the data used, and defines important variables. Section 5 presents the RD design in detail, showing how eligibility for school attendance can be a strong and valid instrumental variable. Section 6 reports the effects of school on different weight measures, diet, and children's time use. Section 7 shows subgroup analysis. Section 8 presents conclusions.

[3] In countries like Japan and Germany, children typically start school at the age of six. There are also countries which have earlier school entry age thresholds, e.g. the United Kingdom, where children enter school at the age of five.

2 Literature Review

This literature review summarizes the factors that relate to school children obesity. Cawley (2010) offers a comprehensive summary on the recent progress on general childhood obesity. Taking an intellectual debt, here I abstract some of his key points and relate to the findings in this paper about school children, complementing them with a discussion on the literature on school lunches. A discussion on the school environment in Australia follows.

2.1 Obesity-Causing Factors

Drop in Food Prices First of all, he first reports that food prices has dropped significantly over time (Christian and Rashad, 2009), and that could increase food intake; in particular, Beghin and Jensen (2008) find that, due to the drop in the price of sugar, soft drink producers tend to substitute high-fructose corn syrup for sugar. Together with my findings that Australian children in school are more prone to sugary drinks intake, the empirical evidence leads to a conclusion that the increased obesity rate among school children can be due to the exposure to affordable sugary drinks.

Advertising Another possible channel is through advertising (Cawley and Kirwan, 2011): producers who receive agricultural price supports need to engage in commodity-specific advertising; these funds are often used to promote fast-food menu items. Unlike children at home who stay under the monitoring of parents, children in school may have more free time during lunch breaks and the transit between home and school. Henceforth children at school are more likely to be attracted by the advertisement.

Substitutes for Maternal Care A literature finds that that maternal employment is an important determinant of childhood obesity (Anderson et al., 2003; von Hinke Kessler Scholder, 2008; Fertig et al., 2009; Cawley and Liu, 2012). As they argue, a (full-time) working mothers often cannot take care their children properly. Consequently, their children often need to consume prepared foods, instead of having regular meals. Moreover, these children may also be sent to child care; Herbst and Tekin (2011) find that they are are more likely to be obese. The school is, to some extent, an extension of child care for older children. Therefore, it is natural to hypothesize if the school leads to similar childhood obesity effects.

This argument, however, also implies that working mothers could be more likely to send their children to school earlier, it confounds the effect of the school on childhood obesity. To eliminate this confounding influence, the regression discontinuity design becomes necessary.

School Lunches Another literature that this paper covers concerns about school lunches. Woo Baidal and Taveras (2014) review the previous researches on school lunches, which mostly point to a fact that school lunches were once problematic: "[school children] consumed more saturated fat than was recommended, and sodium intake was excessive in all age groups. Children ate more than 500 excess calories from solid fats and added sugars per day.", yet are improving. The literature find a small and sometimes negative effect (Schanzenbach, 2009; Millimet et al., 2010) on different school-level programs (diet reforms), such as the School Breakfast Program (SBP) and the National School Lunch Program (NSLP). More recently, Gundersen et al. (2012) uses a more advanced non-parametric, partial identification strategy that handles non-random selection and misclassification errors, finding a mildly positive effect with large bounds. Therefore it is hard to reach a consensus on this issue. The situation is also likely to change as the school lunch improves in quality over time.

2.2 The Australian School Environment

In Australia, school lunches are not under centralized supply. In the school canteens, most children buy their own food. Some schools may let the parents to instruct on the food selection for their children, but children largely have their own freedom to choose what they eat.

Australia has some guidelines to the provision of food in school canteens. The Australian Department of Health commenced the National Healthy School Canteens (NHSC) project in 2008. The project develops national guidelines to the school canteens on the making of healthy food. The guideline offers detailed recommendations on the types of food, the number of servings, the amount per serving. In each state and territory of Australia, there are specific guidelines as well. For instance, the New South Wales government develops the Fresh Tastes Strategy which is mandatory for all public schools in the state. For non-government schools, The Catholic Education Commission and Association of Independent Schools both expressed their support to the program. In an evaluation report, it states that "nearly all (98%) of the Canteen Managers surveyed reported that they had made all or some of the changes to meet the requirements of the Strategy". In a descriptive study, it is noted that although positive effects are evident, the degree of implementation vary (Ardzejewska et al., 2013). The situation in other provinces are similar. A list of state-level guidelines are listed below in Table 1.

In more recent years, a few states have started to impose a ban on sugar sweetened beverages. For instance in NSW, a ban on selling sugar sweetened beverages was imposed in 2007. However, violations of the rules are reported and the ban has only been imposed in government schools. Catholic and private schools only indicated that they encouraged such changes. Drinks are classified as "green" , "amber" or "red" in school. Under the ban, only some sugar sweetened drinks categorized as "red" can no longer be sold in school canteens and vending machines [4]. This leaves a lot of room for sweetened drinks to be still available in the school environment.

[4]For example, sugar sweetened drinks with less than 100kJ per serve and less than 100mg of sodium per serve can still be offered.

Province	Program
New South Walves (NSW)	Fresh Tastes Strategy
Australian Capital Territory (ACT)	National Healthy School Canteens Guidelines
Victoria (VIC)	School Canteen and Other Food Services Policy
Queensland (QLD)	Smart Choices
Western Australia (WA)	Healthy Food and Drink
South Australia (SA)	Right Bite Strategy
Northern Territory (NT)	Northern Territory Canteen, Nutrition and Healthy Eating Policy
Tasmania (TAS)	National Health School Canteens Guidelines

Table 1: Australian Provincial-Level School Canteen Guidelines

3 Background

3.1 Education System in Australia

In Australia, different states and territories have their own school entry age policy. The number of intakes in a school year and the name of the first year of formal schooling also varies across states. The following table summarizes the school entry age cutoffs of each state and territory.

State or Territory	First Year of School	Eligibility (Child turns 5 by)
Australian Capital Territory	Kindergarten	April 30
New South Wales	Kindergarten	July 31
Northern Territory	Transition	Within the year
Queensland	Year 1	January 1
South Australia	Reception	Within the year
Tasmania	Preparatory	January 1
Victoria	Preparatory	April 30
Western Australia	Pre-primary	June 30

Table 2: School Entry Age Rules in Australia

In most states, there is a single intake in a school year, except for South Australia and Northern Territory. In those two states, children only have to be five years old at the beginning of a school term. Due to limitation of survey data in which interviews are administered at a certain time of a year, it is not possible to determine the accurate school entry age for those children in the two states.

As Table 2 shows, most states allow children to enter the first year of formal schooling when they turn five years old in a year. In my paper, I include children from the following four states: New South Wales (NSW), Victoria (VIC), Western Australia (WA), and Australian Capital Territory (ACT). As mentioned above, I do not include children from Northern Territory and South Australia due to the multiple school intakes in a year. As for Queensland, there is only one single intake but there was no formal pre-Year 1 program, and so most children start their first year of school at an older age. The four states I analyze on have similar school entry policies, in which they are have one single intake in a year and the first year of formal schooling is of a kindergarten, pre-Year 1 level. The relationship of school cutoff dates and school attendance is shown in Section 4.

3.2 Discussion on Common School Starting Age Across States and Territories

A common school entry age across all Australian states and territories has been debated among by educators. At the Ministerial Council of Education, Employment training and Youth Affairs, a suggestion of a uniform age ranging from four years five months to four years eight months for school eligibility is discussed in a review (Solutions, 2006; Edwards et al., 2011). This in general makes children eligible to be at school at a younger age. More recently in the media, education experts call for a uniform, yet older school starting age. The Australian Primary Principals' Association proposes that the standardized age across all states and territories to be five and a half years. For instance, in New South Wales, children can start school as young as 4 and a half years old. Under the proposed rule, children would instead be at least 5 years old to be permitted to start kindergarten. A major focus is on how school exposure affects children in terms of cognitive, non-cognitive, and health development. Suziedelyte and Zhu (2015) provide evidence on Australian context that an early school start tends to increase cognitive skills, but reduces non-cognitive skills. It is unclear yet whether school exposure can significantly affects physical health of children in terms of weight outcomes. My paper addresses this issue.

4 Data

This paper uses the data from the Longitudinal Survey of Australian Children (LSAC). The LSAC tracks a nationally representative group of Australian children and their families biannually, starting from year 2004. There are two cohorts in the data: the Kindergarten (K) cohort which includes children born between March 1999 and December 1999, and the Birth (B) cohort which has children born between March 2004 and December 2004. The B cohort is of less than 1 year old by the time the survey begins, so there is considerably more information on activities, diet and family conditions of those children upon birth compared with the K cohort. Overall, the data from both cohorts allow me to study the effect of early school start at age 4-5 (which happens at Wave 1 of K cohort data and Wave 3 of B cohort) on children's weight outcomes at age 6-7 (two years later). Table 3 summarizes age of children at each wave of interview of both cohorts.

	Wave 1 (2004)	Wave 2 (2006)	Wave 3 (2008)	Wave 4 (2010)	Wave 5 (2012)
K Cohort	4-5 Years	6-7 Years	8-9 Years	10-12 Years	12-14 Years
B Cohort	0-1 Year	2-3 Years	4-5 Years	6-7 Years	8-10 Years

Table 3: Age at Each Wave of Interview

As explained in Section 3, my sample consists of children in the following four states and territories: New South Wales (NSW), Victoria (VIC), Australian Capital Territory (ACT) and Western Australia (WA). The attrition rate from one wave to another is small. There is no evidence of joint significance of demographic and socioeconomic factors (such as number of siblings, parents' age, language spoken at home, and household income) on attrition [5].

In the data, there is a clear discontinuity of school attendance across the cutoff dates for all four states. A significant increase of the percent of children who are at school

[5] Results are available upon request.

exists. While NSW has the least increase in percent of children who start school, the jump is still very obvious. In Section 5, I will discuss the estimation strategy of using eligibility for school entry as an instrumental variable (IV) for school attendance. Plots of school attendance rate against age of children will be shown to show the discontinuity.

Apart from measures of weight outcome, the LSAC contains questions related to the diet of children. Another useful feature of the LSAC is the availability of children's time-use diaries. The Time Use Diary (TUD) records children's activities in a day which can be used to construct exercise time variables in my analysis.

4.1 Children's Weight and Obesity Measures

4.1.1 BMI and Weight Status

The focus of this paper is on the physical health of children, in particular their weight outcomes. Body mass index (BMI) is defined as weight (in kg) divided by squared height (m^2). At each wave of the data, interviewers were instructed to measure the study children's weight in light clothing to the nearest 50g, by using glass bathroom scales (Wake and Maguire, 2012). Height on the other hand was measured twice without shoes, to the nearest 0.1 cm. A portable rigid stadiometer was used. Whenever the two height measures differed by more than 0.5 cm, another measurement was taken and the average of the two closest figures are used to construct an average. Otherwise, the average of the first two measurements are used. To assess weight status, the children are classified as normal weight, overweight, or obese according to the International Obesity Taskforce (IOTF) BMI cutoffs (Cole et al., 2000), and similarly using Cole et al. (2007) for underweight cases. The cutoffs are gender and age specific. Unlike the case of adults, for each gender the cutoffs change according to the age of children [6]. My paper focuses on normal, overweight, and obese children [7].

[6] See the Appendix for the age and gender-specific cutoffs for girls and boys

[7] Only around 5% of children are underweight in the data. Children who are classified as underweight in Wave 1 or Wave 2 are not included in my sample.

4.1.2 Waist-to-Height Ratio

This paper is the first to study the causal impact of school on waist-to-height ratio (WHtR). There are studies in the medical literature which suggest that waist-to-height ratio (WHtR) is a better measure of central obesity, and a better predictor for diseases associated with abdominal fat (e.g. Type II diabetes). It also excels in predicting cardiovascular diseases in children compared to using BMI (Savva et al., 2000). In particular, WHtR is described as an easy and non-age-dependent index for screening overweight and obesity in children (Yan et al., 2007). A systematic review by Browning et al. (2010) concludes from 28 studies that the mean boundary values for WHtR from 14 different countries (which include Caucasian, Asian, and Central American subjects) is 0.5. The fact that WHtR adjusts waist circumference for height offers a single useful boundary value for difference ethnic, age and gender groups. Though there are recent attempts which suggest that WHtR should still have gender, age and population group specific cutoffs; there is no updates on Australian children of the age range of my study as of today. Therefore, throughout the paper I am using 0.5 as the cutoff, which is the commonly used boundary value.

4.2 Diet and Time Use

Apart from weight outcomes, my paper is the first to study intermediate outcomes as diet and exercise time of children, which are considered to be main contributors to weight outcomes in the medical literature. While studies have shown that poor diet (e.g. exposure to junk food), lack of physical activities, and high amount of sedentary hours can contribute to higher weight of children, there is so far no studies done on the causal impact of school on them. For instance, Anderson et al. (2011) have shown the impact of school on BMI and overweight/obese status in the case of the United States, yet no analysis was done on the above factors. The LSAC on the other hand, provides sufficient information for these to be studied individually.

The LSAC provides two 24-hour time use diaries of children, one on a weekday and another on a weekend. The activities are finely categorized, which provides great details on time use of children in terms of physical activities and sedentary behaviors. As children start to spend a significant amount of time at school, whether they have appropriate amount of active time at school depends on the school environment and the curriculum. There can also be substitution between school and parental exercise time (e.g. if a child spends a lot of active time at school, he/she may tend to engage in less physical activity with parents). It is therefore important to study whether the overall active time changes. In terms of diet, during each interview, parents are asked how many servings the child has had a certain type of food in the past 24 hours. Though a serving does not necessarily convert to a standardized amount (as people may have different ideas of how large a "serving" is), the questions give an idea of how often a child has had different categories of food; or at least, whether a child has exposure to certain types of food. Junk food exposure can be a contributor to heavier weight. The LSAC provides information on the exposure to sugar sweetened beverages, as well as food items with a high fat content. Upon school entry, children start to spend a large amount of time at school. A change from the home environment to school may cause a significant change in diet and exposure to different food categories. In Australia, there is no official school lunch policy, but tuck shops, vending machines or school canteens are available. The fact that there is a shift of a large amount of time from being at home to in school poses a risk on children's exposure to junk food.

4.2.1 Diet

In the main survey, parents are asked how many times a child has eaten certain categories of food items in the last 24 hours. The questions include a broad spectrum of food items.

Food items which are considered as having high fat content include the following:

- Biscuits
- Pie

- Hot chips or french fries
- Potato chips or savoury snacks

The above items cover most of the commonly consumed high fat food of Australian children. Portion size is not mentioned in the data, and if any, it is highly debatable to have a common consensus of what is "one serving". Lumping the answers of the above "fatty food" categories, I construct a variable summarizing the number of times a child consumes fatty food [8].The majority of children have had at least some fatty food items. It is rarely a case that one has not had any in a day.

Sugar sweetened beverages on the other hand include soft drink or cordial. It is asked in one single question in the interview. I again construct a categorical variable summarizing whether a child has any exposure to them. In addition, at the intensive margin another categorial variable summarizes the options of: none, once, or more than once a child has had sugary drinks in a day.

4.2.2 Time use: Exercise and Active Time

LSAC collects time-use diary (TUD) of the study children over two separate days. The design aims for offering two 24-hour diaries, one on a specified weekday and another on a specified weekend day. The diaries were distributed after the interview, with the interviewer showing how to complete a diary to the respondent. Though the respondent received suggested dates to complete the diary, it can be the case that it is not followed. As such, the suggestion was to complete it on the same day in the next week. The objective of random allocation of days in a week was to have an even distribution among the 7 days in a week. Activities are recorded in 15-minute intervals, with 26 options of activity to choose from. The diaries also indicate the location which the activity took place (5 choices), and the person(s) the activity was done with (7 choices). As children were relatively young during the interview period, diaries were completed by adults (mostly the child's mother).

[8]In each of the question, the answer options are: not at all; once; and more than once.

As children grow, the types of activities they might pursue became different. For example, the activity choices in age 4-5 and age 6-7 are not the same (but the diary design remains consistent across the two cohorts). In the Appendix, a sample diary of each age is given.

To construct time use variables, I focus on the time spent on physical activities. The time spent measured is converted to hours, with the time in the weekday diary multiplied by 5, and that in a weekend diary multiplied by 2. These represent the weekly active hours. To ensure that the time measure is a good representation of weekly time spent, only observations which consist of one weekday and one weekend diaries are included.

At age 4-5, children are young and physical activities in this paper can include moderate activities such as walking. As suggested by the Australian government, children of this age range should have at least 3 hours per day of active time, which amounts to 21 hours per week. The guideline does not only limit to vigorous sports as children are relatively young and generally do not participate in organized sport activities. In my paper, the activities included are:

- Walking (for travel or for fun)
- Riding bicyle, trike, etc.
- Active free play or other play/activities
- Organized lessons/activity
- Other exercise: swim/dance/run about
- Visiting people, special event, party
- Taken places with adult (e.g. shopping)

5 Estimation Strategy

5.1 Validity of RD design

5.1.1 School Entry Rules and Timing of School Entry

Fig. 1 shows the plots of percentage of children in school against the months away from the corresponding cutoff for each state or territory. It shows that indeed the school entry rules strongly affects the percentage of children who enter school. The highest compliance rate occur in WA. The percentage of in-school children increases significantly at the cutoff. The lowest compliance occurs in NSW. Regardless, school entry rules have strong correlation with the timing that children attend school across all states. The required monotonicity assumption in a regression discontinuity design is satisfied. This shows the validity of using school eligibility of children as an IV for school entry in the subsequence analysis in this paper.

5.1.2 Exogeneity Assumption

The validity of a RD design relies on no manipulation of birth timing of children around the cutoff. In particular, parents may tend to manipulate the timing depending on family and child characteristics. In the US, Dickert-Conlin and Elder (2010) find that there is no discontinuity in the number of births at the cut-off. In my paper, I check by plotting the density of age in months away from the cutoff. Note that in the case of discrete running variable (where age is not continuous in my data), using a standard Mccrary test for discontinuity is not appropriate. In particular, Mccrary test relies on local linear regression (Lee and Card, 2008). Presented below is a density plot. There is no observed discontinuity at zero (i.e. the cutoff).

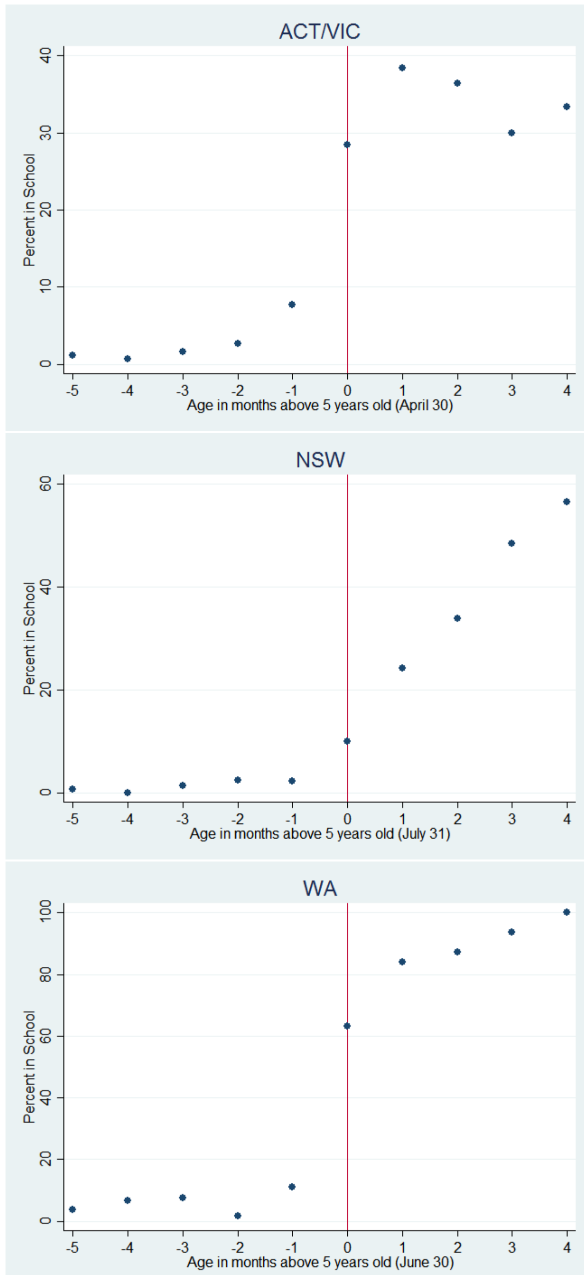

Figure 1: Effects of school cutoff rule on school attendance in ACT/VIC, NSW and WA

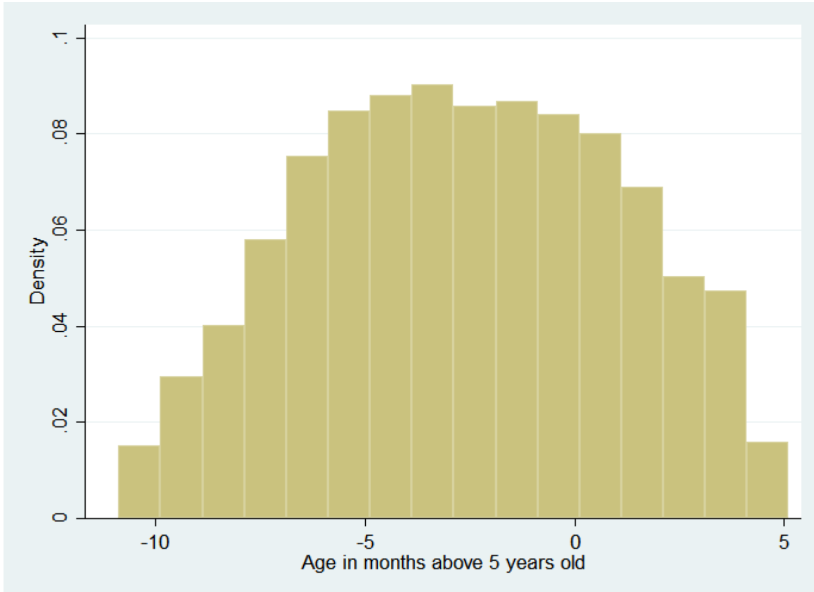

Figure 2: Density plot of children's age above cutoff

Further, I also investigate the following: household income per child, mother's education, main language spoken by study child at home, and child's birthweight. As observed in Fig. 3, the mean value of each variable is plotted against children's age. There appears to be no discontinuity in any of the above covariates. Therefore, it is highly unlikely the case that there is any selection.

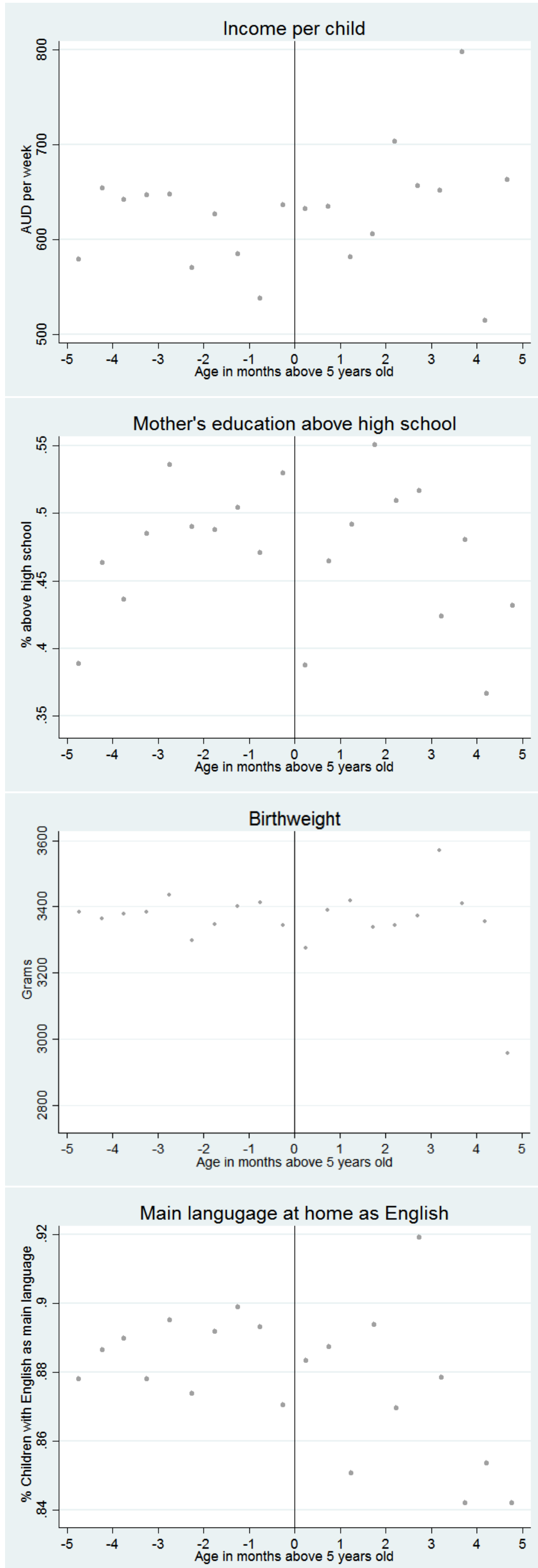

Figure 3: Plots of family and child characteristics against child's age above cutoff

5.2 Econometric Specification

Consider an estimation equation showing the relationship between the outcome variable Y_i and school attendance Sch_i:

$$Y_i = \gamma_0 + \gamma_1 Sch_i + \gamma_2 X_i + \epsilon_i \tag{1}$$

Where Sch_i is a binary variable which takes the value of 1 if a child begins school early, and 0 otherwise. X_i includes other control variables which includes gender, state fixed effects, and age deviation from the cutoff date. Alternatively, there can be interaction terms of the control variables with Sch_i to allow for heterogeneous treatment effect.

As described in Table 2, an Australian child is eligible to attend school only when she turns five years old by a certain cutoff date (which varies by states and territories). As the probability of school attendance does not jump from zero to one at the cutoff, it is a fuzzy regression discontinuity (Imbens and Lemieux, 2008) design.

School attendance itself can be endogenous. For instance, children who come from a disadvantaged background (e.g. low income families) may tend to be in school earlier for parents to avoid childcare costs. The casual impact of school attendance on an outcome can be found by using a binary instrument of whether a child is eligible for school at a year to instrument for school attendance. A child is considered to be eligible if she turns age five by the cutoff date in the state she resides in. The different age cutoffs in each state is listed in Table 2. The first and second stages of estimation are:

$$Sch_i = \alpha_0 + \alpha_1 \mathbb{1}(age_i \geq 5) + \alpha_2 X_i + f(age_i - 5) + \zeta_i \tag{2}$$

$$Y_i = \beta_0 + \beta_1 Sch_i + \beta_2 X_i + g(age_i - 5) + \eta_i \tag{3}$$

where f and g are polynomials in the running variable of age. However, due to the nature of the data in which the exact birth dates are not known, the age information available is in months. This leads to a case of discrete running variable and using high order flexible polynomial can lead to a collinearity problem [9]. The solution adopted here is to non-parametrically control for age effects, and use age in months dummies as in (Suziedelyte and Zhu, 2015). To avoid perfect collinearity with the indicator for school eligibility and the constant term , the dummy for the month just before and after the cutoff are treated as baseline dummies.

Note that the first stage equation involves a binary dependent variable of school attendance. As pointed out by Baum et al. (2012), the usual approach of using linear probability model (LPM) in the first stage regression is not appropriate. One well known flaw is that the fitted values are not confined to the unit interval. Predicted probabilities can then be above one or below zero. Though some support the idea that LPM is easier to be implemented and works fine for values near the averages in the sample (Wooldridge, 2010; Angrist and Pischke, 2008), Lewbel et al. (2012) have shown that LPM cannot even give the correct sign of the treatment effect in a simple example in their paper. The "wrong" effect can even be found to be statistically significant, leading to an incorrect conclusion in the opposite direction.

In my paper, I opt to use a "probit two-stage least squares (probit-2sls)" approach proposed by Cerulli et al. (2012) when the outcome variable of interest Y_i is continuous. This involves a first stage probit regression, and using the fitted probabilities I perform standard two stage least square as the second stage. Standard errors are adjusted.

When instead the outcome variable is binary, I adopt a bivariate probit model. It is used for estimations with weight status as the dependent variable (e.g. whether a child is obese or not). The identifying assumption is an exclusion restriction, that $\mathbb{1}(age_i \geq 5)$ is not included in the list of independent variables in the outcome equation. In particular,

[9] It is found that age, age^2 and higher order terms of age are highly collinear.

the equations become:

$$Sch_i^* = \alpha_0 + \alpha_1 \mathbb{1}(age_i \geq 5) + \alpha_2 X_i + f(age_i - 5) + \zeta_i \tag{4}$$

$$Y_i^* = \beta_0 + \beta_1 Sch_i + \beta_2 X_i + g(age_i - 5) + \eta_i \tag{5}$$

in which the latent variable Sch_i takes the value of 1 if $Sch_i^* > 0$ and 0 otherwise. Similarly, Y_i takes the value of 1 if $Y_i^* > 0$ and 0 otherwise. The error terms are assumed to follow the joint normal distribution:

$$\begin{bmatrix} \zeta_i \\ \eta_i \end{bmatrix} = N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \tag{6}$$

where ρ represents the correlation between ζ_i and η_i. As ρ can be non-zero, the estimation calls for a simultaneous estimation by Maximum Likelihood of the two equations (4) and (5). The log-Likelihood function can be found in p.123 of Maddala (1983). The estimation is unbiased even in the presence of an endogenous independent variable in the outcome equation (Greene and Hensher, 2010).

6 Results

This section presents the results of the estimations outlined in the previous section. Note that all t-statistics in the regression of school attendance on whether a child is eligible for school exceeds 4.5 in all cases. To avoid including children who are too far away from the cutoff, only children five months above and below the cutoff date are included [10]

[10]The maximum number of months above the cutoff in the data is 4.98. This serves as a guideline for choosing the lower bound on the left of the cutoff.

6.1 Weight and Obesity Measures

6.1.1 BMI, Overweight Status, and Obesity

The impacts of school on BMI, probability of overweight, and probability of obese are presented in Table 4. The results for the K Cohort and B Cohort are shown respectively in columns (1)-(3) and (4)-(6). When merging the two cohorts, the result is shown in Table 5 instead. Note that across all regression results, school eligibility is statistically significant in the "first-stage" regression which school attendance is the dependent variable.

In all the columns which BMI is the dependent variable, a probit two-stage-least squares estimation is implemented as discussed in Section 5. In the columns which probability of overweight or obese is studied, a bivariate probit estimation is adopted. Therefore, an additional row showing the probit average treatment effect (ATE) is shown for those cases.

In the available data, the maximum age of children who are eligible for school is 4.98. To avoid including children who are too young and far away to the left from the cutoff, in each panel, I include observations which are within 5 months away from the cutoff date on the left. In all specifications, dummies of age in months (away from cutoff) and state fixed effects are included. There is no need to include other control variables given the RD design. Instead, subgroup analysis will be discussed in Section 7 to allow for different constant terms and slope estimates for specific groups (in terms of gender, types of school attended etc.). In particular, it is reasonable to believe that the marginal effects for boys and girls can be different.

	K Cohort			B Cohort		
	Panel A: Instrumental Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
	BMI	Prob (Over)	Prob (Obese)	BMI	Prob(Over)	Prob(Obese)
In School Early	0.205	0.474	1.183***	0.205	0.652*	1.413***
	(0.624)	(0.425)	(0.405)	(0.624)	(0.390)	(0.396)
Mean (dep. var.)	16.77	0.208	0.059	16.77	0.210	0.068
Std (dep. var.)	2.103	0.405	0.235	2.103	0.408	0.251
Probit LATE		0.147	0.230		0.214	0.352
	Panel B: First Stage					
	(1)	(2)	(3)	(4)	(5)	(6)
	Prob(School)	Prob(School)	Prob(School)	Prob(School)	Prob(School)	Prob(School)
Eligible for School	0.540***	0.525***	0.555***	0.540***	0.680***	0.706***
	(0.136)	(0.140)	(0.133)	(0.136)	(0.141)	(0.141)
	Panel C: Reduced Form					
	(1)	(2)	(3)	(4)	(5)	(6)
	BMI	Prob (Over)	Prob (Obese)	BMI	Prob(Over)	Prob(Obese)
Eligible for School	0.125	-0.098	0.208	0.125	0.104	0.169
	(0.200)	(0.135)	(0.202)	(0.200)	(0.137)	(0.197)
Number of Obs.	1872	1872	1872	1760	1760	1760

Table 4: BMI, Probabilities of Overweight or Obese at Age 6-7

K and B Cohorts:

In Table 4, columns (1) and (4) show the impact of school on the mean BMI at age 6-7. Columns (2) and (5) present the effects on the probability of overweight. Overweight is defined as the status which a child is considered to be so, depending on the age and gender specific cutoffs [11]. Overweight in this paper is defined as a category which includes all children passing the overweight cutoff (i.e. including obese children). Columns (3) and (6) show the effects on the probability of obese.

As observed in Panel A columns (1) and (4), the effect of school on BMI is positive yet statistically insignificant. Columns (2) and (4) show that the effect on the probability of overweight is positive. It is statistically insignificant for the K Cohort, and significant at 10% level for the B Cohort. In terms of magnitude of the school effects, it is greater for the B Cohort. For the B Cohort, children who enter school early are 21.4% more likely to be overweight. For the K Cohort, early entrants are 14.7% more likely to be so. The probability of obese is shown to be positive and statistically significant in both column (3) and column (6) at 1% level. Note that economically the effects are also significant. For the K Cohort, children who enter school early at age 4-5 are 23.0% more likely to be obese at age 6-7. The effects for the B Cohort is even larger at 35.2%.

Overall, it is observed that the effect on BMI and the probabilities of overweight and obese are larger for the B Cohort than that of the K Cohort. However, it is shown that both cohorts display similar pattern that the mean BMI does not change significantly, yet the probability of obese increases for children who enter school early.

[11] The specific cutoff values of BMI for overweight and obese status are shown in the appendix

Table 5: Merged: BMI, Probabilities of Overweight or Obese at Age 6-7

	Panel A: Instrumental Variable		
	(1)	(2)	(3)
	BMI	Prob (Over)	Prob (Obese)
In School Early	0.388	0.485*	1.203***
	(0.444)	(0.280)	(0.290)
Mean (dep. var.)	16.77	0.209	0.063
Std (dep. var.)	2.153	0.407	0.243
Probit LATE		0.153	0.259
	Panel B: First Stage		
	(1)	(2)	(3)
	Prob(School)	Prob(School)	Prob(School)
Eligible for School	0.613***	0.605***	0.619***
	(0.981)	(0.099)	(0.096)
	Panel C: Reduced Form		
	(1)	(2)	(3)
	BMI	Prob (Over)	Prob (Obese)
Eligible for School	0.191	0.001	0.186
	(0.147)	(0.096)	(0.141)
Number of Obs.	3632	3632	3632

Merged:

The two cohorts of children display similar pattern in weight outcomes. Merging the cohorts, the results remain to be very similar in Table 5: a small, positive but insignificant change in the mean BMI;, a moderate increase in the probability of being overweight, and a very significant impact on the probability of obese [12]. In particular, early school entrants are 25.9% more likely to be obese, and the result is significant at 1% level. Overall, it is safe to conclude that school has a positive and significant impact on the probability of obese. The merged data provide enough observations to redo the above in a more localized approach. Limiting to children only 3 months above and below the cutoff, the result on the probability of obese is even stronger. Children who enter school early are 33.7% more likely to be obese (statistically significant at 1% level). If including children who are just 1 month away from the cutoff, the result remains to be robust.

[12] Due to the nature of the data the running variable is discrete. For completeness, standard RD plots of the probabilities of overweight and obese are still presented in the appendix.

Early school entrants are 39.3% more likely to be obese (statistically significant at 1%).

The fact that the two cohorts have similar pattern in weight change from age 4 to 6 serves as a justification for merging the two in subsequence analysis. Though not entirely ideal, this step is necessary as a solution to the low number of observations in the data. Since time-use diaries are not readily available from all children, it is critical to do so in order to do any analysis on exercise habits, as well as subgroup analysis.

Distributions of BMI:

Tables 4 and 5 have shown that the effect of school on mean BMI is minimal. It is important to note though, a regression of the average BMI may not present the whole picture. The fact that the probability of obese shows a significant result calls for a comparison of the distributions of BMI between the "in school early" vs. "not in school early" groups.

A way to understand the difference between the "in school early" group vs. the "not in school early" group is to compare their BMI distribution plots. It is unfortunate that the K Cohort starts with data when children are aged 4-5. However, the B Cohort contains information of BMI when children are only aged 2-3. It is therefore possible to see whether early and late entrants differ 2 years before the school entry year.

Figure 4 presents the distributions of BMI of the two groups at the time before school, i.e. BMI at age 4-5, BMI at age 2-3; and that of birthweight. The longer green dashline at each BMI graph represents the cutoff for overweight, and the purple one represents that for obese status [13]. Across all the distribution plots, the two groups display no significant difference in all the "pre-school" periods. There is minimal difference at age 4-5, the time which the early entrants have just started school for less than a year (school usually starts at January to February in Australia, and the interviews began in April). Potentially, any positive impact on weight would be present for the early entrants, making the two groups a bit less similar. When looking at age 2-3 (two years before the entry year), early entrants are also very similar to that of late entrants in terms of BMI

[13] The overweight and obese cutoffs are gender and age specific. The average cutoff values are shown in the graphs.

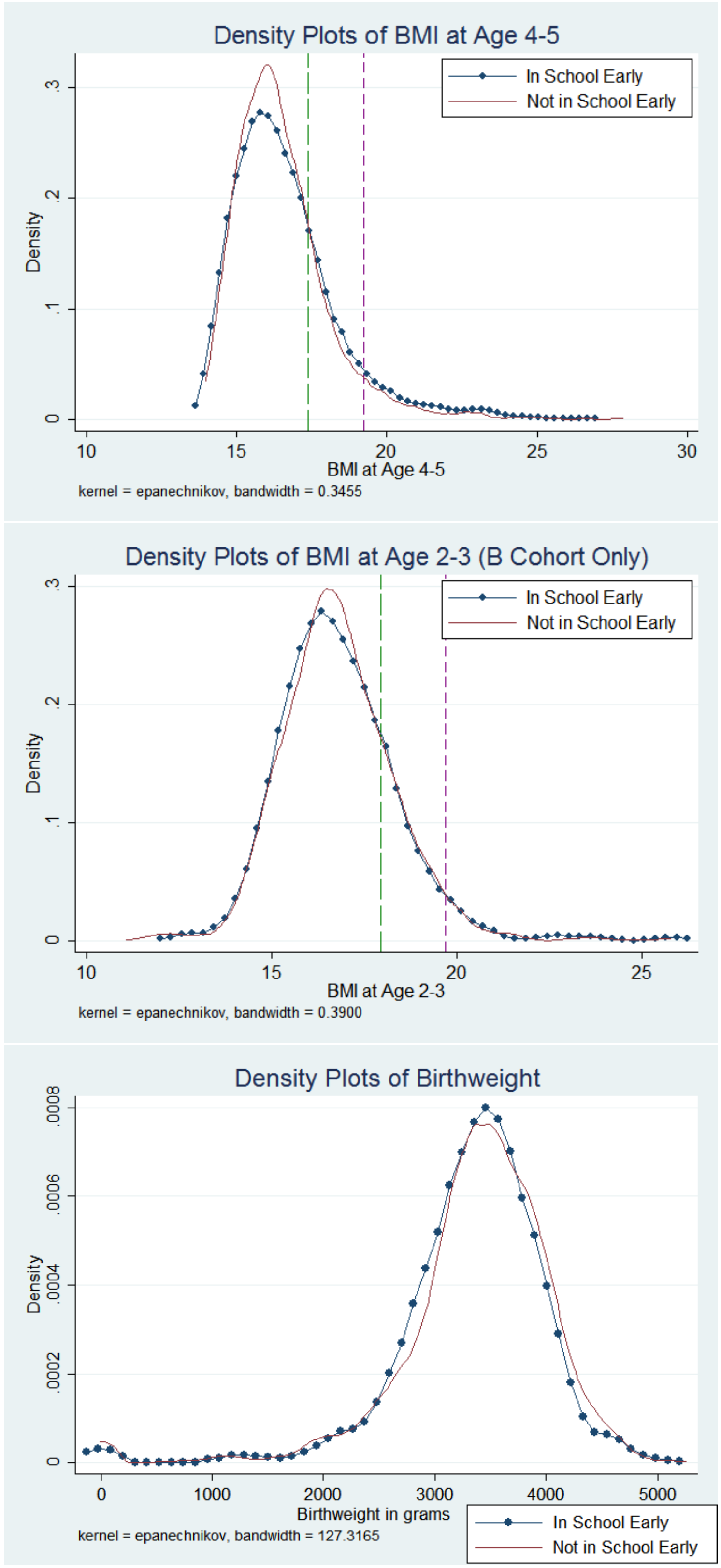

Figure 4: Distributions of BMI at or before School Entry Year, and Birthweight

distribution. Moving to an even earlier period, the birthweight distributions of early and late entrants are similar. In fact, if any, the early entrant group is slightly lighter in terms of birthweight. Regardless, standard first-order stochastic dominance tests have found no significant difference in the distributions between the two groups of children.

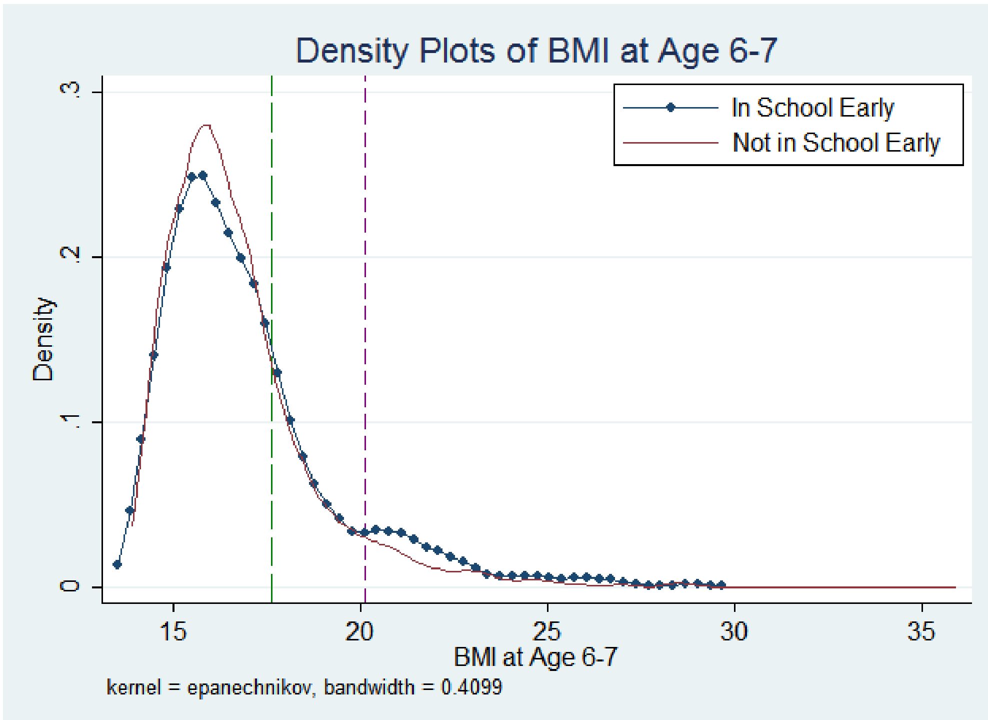

Figure 5: Distributions of BMI at Age 6-7

As observed in Fig. 5 , there is significant difference between the two groups at age 6-7, in which the "in school early" group tends to be more likely to be obese. In particular, the distribution of the "in school" group display an extra "hump-shape" region to the right of the obese cutoff. The first-order stochastic dominance test rejects the null hypothesis that the distributions of early and late entrants are identical at 5% significance level [14].

The idea is that though there may be no significant change in mean BMI due to school. However, there can still be difference in the BMI distribution, which essentially affects the likelihood for children to be passing the obesity cutoffs. Fig. 4 and Fig. 5 offer an explanation to the regression results in Table 5, in which no significant change is found

[14] In fact, the p-value is close to 1%.

on the mean BMI, whereas there exists a significant impact of school on the probability of obese.

6.2 Waist-to-height Ratio

	(1) 5 Months from Cutoff	(2) 3 Months from Cutoff	(3) 1 Month from Cutoff
In School Early	0.695*** (0.251)	0.691** (0.279)	0.751* (0.436)
Mean (dependent variable)	0.191	0.185	0.191
Std(dependent variable)	0.393	0.388	0.393
Probit LATE	0.218	0.212	0.233
Number of Obs.	3663	2392	859

Table 6: Waist-to-Height Ratio at Age 6-7 (Within 5 Months away from Cutoff)

As we can see in Table **??**, the impact of school on waist-to-height ratio at age 6-7 is presented. As discussed in Section 4, children are recommended to have a waist-to-height ratio (WHtR) not exceeding 0.5. The two cohorts are merged together. To be concise, I present here the IV regressions in one table, summarizing the results when limiting to 5 months away from the cutoff in Column (1), and 3 months only in Column (2) [15]. The coefficients are very similar in both cases, with 1% and 5% statistical significance respectively. When further limiting to only 1 month away from the cutoff in Column (3), the result remains to be similar in magnitude, with significance 10% . Across all the columns the probit LATE effect shows that children who are in school earlier tend to be more likely to be having a WHtR exceeding 0.5. The effect ranges from 21.2% to 23.3%.

It is of significant health concerns of children as central abdominal obesity can be detrimental, and highly associated with risk of heart attack and other obesity-related cardiovascular diseases (Savva et al., 2000). Moreover, as mentioned in Section 4, WHtR is considered as another measure of obesity. The fact that a positive significant impact of school on the likelihood of WHtR exceeding 0.5 matches with the BMI results in Table 5.

[15]The first-stage results are similar to that of Table 5, showing that school eligibility is a strong IV for school entry. Results available upon request.

Using either measure, children who are in school tend to be more likely to be obese after 2 years. Again, I present here the comparison of the density plots of the "in school early" vs. "not in school early" group on their WHtR at age 6-7. The reference line is at 0.5 for the plots at age 6-7. However, at age 2-3, children are of a very young age and there is no common consensus as to a threshold value of the ratio. As a result, no reference line is shown in the corresponding diagram.

Again one way to see the change in WHtR is to compare the distribution of it before and after the entry year. In Fig. 6 the distributions of WHtR at age 2-3 and 6-7 are shown respectively. At age 2-3 [16], early and late school entrants display a very similar distribution of WHtR. If any, the early entrants are having smaller WHtR than late entrants in general. However, at age 6-7, there exists a difference between late and early entrants. Those who enter school early tend to be more likely to have WHtR exceeding 0.5. A first-order stochastic dominance test rejects the null hypothesis that the two distributions are equal at 10% significance level.

[16] Only WHtR of cohort B is available. As explained before, at the first wave of data of the K cohort children are already at age 4-5.

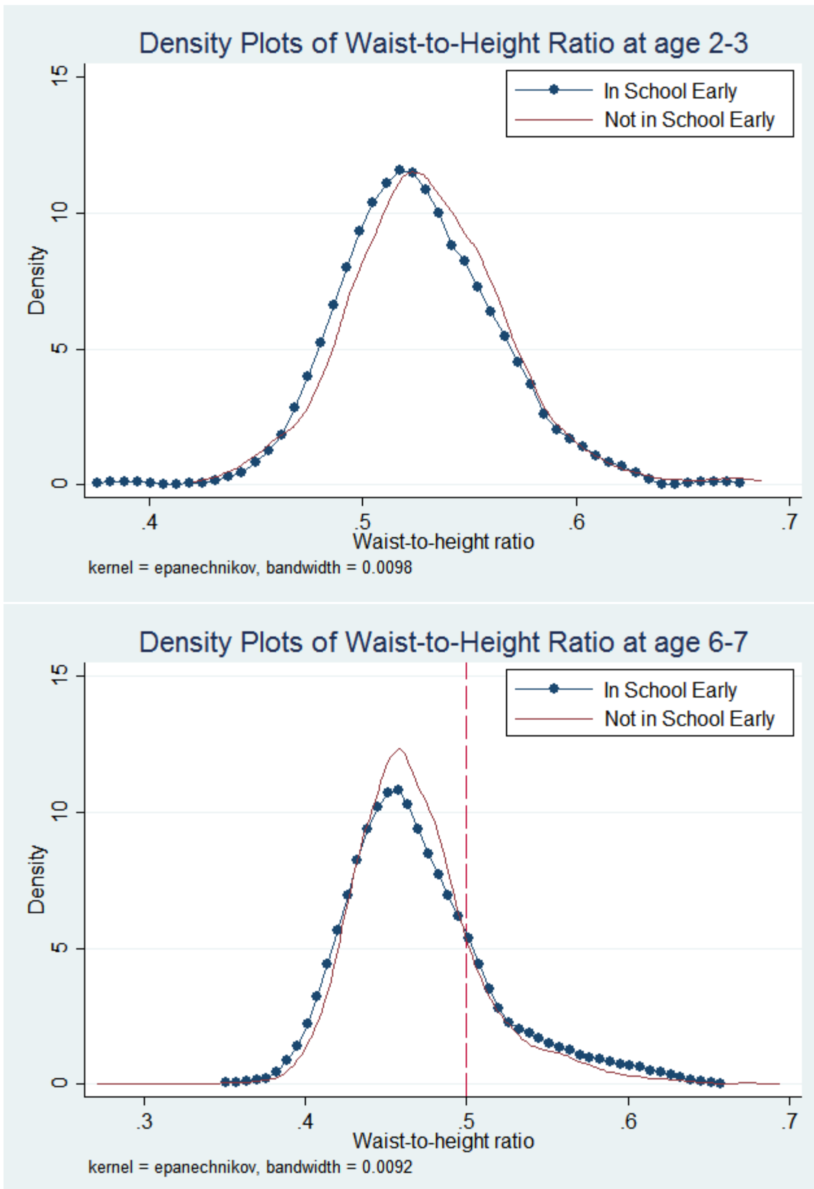

Figure 6: Distributions of WHtR at age 2-3 and 6-7

6.3 Diet, Exercise, and Screen Time

6.3.1 Diet at Age 4-5

Sugary Drinks:

The LSAC contains information about children's diet on a particular day in the format of interview questions, asking parents how many times in a day the study child has consumed certain types of food. In particular, sugary drinks and food with high fat content are generally believed to be associated with adverse weight outcomes. The following provides estimates of the impact of school on those food items.

The median consumption of softdrink or cordial in the sample at age 4-5 is 0 times in a day, implying that most children are not yet exposed to sugary drinks at this young age. It is meaningful to see if school entry itself leads to children's exposure to sugary drinks. In Table 7, the dependent variable is binary, which takes the value of 1 when a child consumes more than 0 times of sugary drinks; 0 otherwise.

As observed in Column (1), including children who are within 5 months from the cutoff gives a positive estimate but it is statistically insignificant. Economically, the effect is not small as a 11% increase in the probability of having sugary drinks. Moving closer to the cutoff, Column (2) shows a bigger effect which is statistically significant at 5%. The effect is large as children who are in school are 19.5% more likely to have sugary drinks. The result remains to be robust as only children who are just within 1 month from the cutoff are included. Possibly due to the low number of observations, the result is only 10% significant. However, it is important to note the magnitude of school's effect on sugary drinks exposure is similar and stronger than that of Column (2) at 25.5%.

At the intensive margin, in Table 8 the dependent variable takes the value of 2 if the child consumes sugary drinks more than once; a value of 1 if only once; and 0 otherwise. A bivariate ordered probit estimation is implemented as the dependent variable can take 3 possible values. A similar pattern is found as that of Table 7. When including children who are within a wider range of 5 months away from the cutoff, the effect is not as strong as the other columns. Column (1) shows that the average treatment effects are not strong and of small magnitude. However, when including only children who are 3 months away from the cutoff at Column (2), a stronger effect is found which is significant at 5% level. The effect on the probability of having 0 sugary drinks is -19.3%; that on having sugary drinks once in a day is 5.7%. Children who enter school early are 13.6% more likely to have them more than once. Effects of similar magnitude is found in Column (3) in which a narrower age range of 1 month away from the cutoff is included. Once again the result suffers from the problem of low number of observations, but it is important to note that the estimated effects are of very similar magnitudes as that of Column (2).

	Prob (Consumed softdrink/cordial)		
	(1) 5 Months from Cutoff	(2) 3 Months from Cutoff	(3) 1 Month from Cutoff
In School Early	0.288	0.513**	0.668*
	(0.235)	(0.260)	(0.384)
Mean (dependent variable)	0.364	0.369	0.377
Std(dependent variable)	0.481	0.483	0.485
Probit LATE	0.110	0.195	0.255
Number of Obs.	3660	2391	860

Table 7: Sugary drink exposure at age 4-5

	Ordered Probit: softdrink/cordial		
	(1) 5 Months from Cutoff	(2) 3 Months from Cutoff	(3) 1 Month from Cutoff
In School Early	0.261 (0.228)	0.508** (0.243)	0.515 (0.357)
Mean (dependent variable)	0.517	0.522	0.531
Std(dependent variable)	0.745	0.745	0.748
Prob (Softdrink=0)	-0.099	-0.193	-0.197
Prob (Softdrink=1)	0.033	0.057	0.059
Prob (Softdrink>1)	0.066	0.136	0.138
Number of Obs.	3660	2391	860

Table 8: Ordered probit regression of sugary drink consumption at age 4-5

Food with High Fat Content:

Consuming food items with high fat content, like the case of sugary drinks, can contribute to higher weight of children. As explained in Section 4, fatty food items include the following: biscuits, pie, hotchips or french fries, and potato chips or savoury snacks. Unlike the case of sugary drinks, most children have some exposure to fatty food items (only around 10.6% have none). To summarize the effect of fatty food consumption, a categorial variable is constructed: 0 for zero times of consumption, 1 for once in a day; 2 for two times; and 3 for three or more times. As a result, a bivariate ordered probit estimation is used.

As Table 9 presents, there is no clear evidence of school leading changes to high fat food consumption. The effects in all columns are negative and statistically insignificant. The effect on the probability of each consumption level is presented in the table. Overall, most of the effects are economically insignificant too.

	Ordered Probit: High Fat Food Items		
	(1) 5 Months from Cutoff	(2) 3 Months from Cutoff	(3) 1 Month from Cutoff
In School Early	-0.094	-0.099	-0.437
	(0.196)	(0.252)	(0.327)
Mean (dependent variable)	1.688	1.705	1.704
Std(dependent variable)	0.953	0.952	0.960
Prob (High fat food=0)	0.018	0.019	0.092
Prob (High fat food=1)	0.019	0.020	0.081
Prob (High fat food=2)	-0.009	-0.009	-0.042
Prob (High fat food>2)	-0.028	-0.030	-0.130
Number of Obs.	3649	2382	854

Table 9: Ordered probit regression of high fat food consumption at age 4-5

6.3.2 Time use: Exercise Time

Active Time at Age 4-5

At a young age of age 4-5, the Australian government gives suggestion of the amount of active time per day. Section 4, the included "active" activities included. Note that the activities included are not necessarily high energy expending (such as organized sports which are much more common at an older age).

In Table 10, columns (1) and (2) show the results of the impact of school on the weekly hours of active time. The effects are negative yet statistically insignificant. Columns (3) and (4) instead study whether children meet the threshold of the suggested 3 hours or more of active time per day. As the hours in the data are converted to weekly terms, the corresponding threshold is 21 hours per week. The dependent variable takes the value of 1 if a child meets the requirement, 0 otherwise. As both columns show the effects are negative and statistically insignificant. If anything, school tends to reduce the total active time of children. There is however not enough evidence that the effect is significant.

	(1) Within 5 Months Weekly Hours	(2) Within 3 Months Weekly Hours	(3) Within 5 Months Prob(Weekly Hrs.>=21)	(4) Within 3 Months Prob (Weekly Hrs.>=21)
In School Early	-3.202	-2.485	-0.357	-0.337
	(4.331)	(4.796)	(0.296)	(0.353)
Mean (dep. var.)	30.949	31.043	0.674	0.664
Std(dep. var.)	16.788	17.080	0.469	0.472
Number of Obs.	1969	1307	1969	1307

Table 10: Age 4-5 active time and probability of being active for at least 21 Hours per Week

Concluding from Tables 7-10, children who are in school early tend to be more likely exposed to sugary drinks in both the extensive and intensive margins. This potentially can be a factor contributing to the adverse weight outcomes. On the other hand, there is little to no evidence that school affects high fat food consumption. While generally it is believed that attending school shifts time spent with parents partially to school time, the overall active time of children is not significantly affected. If any, there is some reduction in the active time, but not in a large magnitude that affects of chance of hitting the suggested level of active time by the Australian government. The fact that there is an increased exposure to sugary drinks along with no improvement in active time is likely to contribute to heavier weight of children, or even central obesity as measured by the waist-to-height ratio.

7 Subgroup Analysis

As mentioned in Section 5, the results presented are for the overall sample averages. In particular, one may be especially interested in any significant difference in school's impact on the weight outcomes among different subgroups. For example, boys and girls may experience different effects due to different development profiles over age. Also, the comparison between government vs. non-government schools is of particular interest, as most of the diet guidelines are imposed on the government sector [17].

	All	Boys	Girls	Non-gov't Schools	Gov't Schools	Low Income per Child
In School early	1.203***	1.100**	1.300***	0.991	1.305***	0.960*
	(0.290)	(0.510)	(0.348)	(0.833)	(0.308)	(0.534)
Probit LATE	0.259	0.224	0.289	0.191	0.291	0.177
No. of Obs.	3632	1881	1751	1234	2398	798

Table 11: Subgroups: Probability of Obese

As observed in Table 11, girls tend to be more severely affected by school in the probability of obese (28.9% more likely vs. 22.4% for boys). In comparing government schools vs. non-government schools, an interesting pattern arises. The effect for children who attend government schools is much stronger (29.1% vs. 19.1% in the non-government sector). Despite the fact that guidelines regarding diet are imposed in government schools in Australia, it appears that there is room for improvement. One may worry that is just due to the selection (i.e. children who come from low income families tend to attend government schools). However, as I limit the sample to families which have an income per child below the median, the effect is in fact less than that of the overall sample. Due to the low number of observation, it is understandable that statistical significance is not strong. Regardless, the magnitude of the effect itself is smaller at 17.7% only. It is likely the case that selection of children with low family income cannot fully explain the difference between government vs. non-government schools.

[17]For easy comparison, I list the effect of the whole sample and contrast it with the subgroup results. Non-government schools here include both private and catholic schools.

	All	Boys	Girls	Non-gov't Schools	Gov't Schools	Low Income per Child
In School early	0.695***	0.694*	0.730**	0.388	0.809***	0.571
	(0.251)	(0.392)	(0.333)	(0.615)	(0.281)	(0.556)
Probit LATE	0.218	0.209	0.237	0.108	0.261	0.175
No. of Obs.	3663	1894	1769	1239	2424	804

Table 12: Subgroups: Probability of Having a Waist-to-Height Ratio Exceeding 0.5

Table 12 instead presents the results on the probability of having a waist-to-height ratio exceeding 0.5, the benchmark for central obesity problem. A similar pattern to that of Table 11 is observed. Girls tend to be more heavily affected than boys (ie. 23.7% more likely vs. 20.9%). Again, a comparison between the government schools and non-government schools give the same conclusion. The magnitude of effect is much larger in the government sector (26.1%) than that of the non-government one (10.8%). Limiting to a sample of low income group cannot explain such a difference. The fact that the results from Table 11 and 12 are consistent indicates that government schools in general are doing worse. This points to the direction that more enforcement should be done on the guidelines regarding diet and healthy lifestyles in schools.

8 Conclusion

This paper has found that school contributes to childhood obesity in Australia, and it is likely to be via the channel of increased exposure to sugar sweetened beverages. The evidence suggests that while educators are proposing to unify the school starting age in Australia, in the perspective of countering childhood obesity it can be beneficial to set up a greater age cutoff. It would also be helpful if more attention is paid to enforcing the guidelines regarding sugar sweetened beverages. In recent years, some states have launched a ban of sugar sweetened drinks (e.g. NSW) for government schools. Catholic and private schools have only indicated that they encourage such change in their sectors. Though violations have also been reported in the media, some other states and territories are planning to adopt a similar strategy. As more attention is paid to enforce the rules, they are likely to have positive effect on the current obesity problem.

As my study points out, not only the government can consider modifying the school entry age, more focus should be on improving diet in school. This does not only provide information to the Australian case, but also can be an signal for other countries to realize the importance of limiting sugar sweetened beverages at school. More detailed school level, or classroom level data would be useful in identifying the exact mechanism (e.g. peer effects among students) of the spreading of eating habits at school. Regardless, the results of this paper points to the direction of improving availability of healthy food items instead of unhealthy ones at school.

Appendix

Age (years)	Overweight		Obese	
	Boys	Girls	Boys	Girls
2	18.41	18.02	20.09	19.81
2.5	18.13	17.76	19.8	19.55
3	17.89	17.56	19.57	19.36
3.5	17.69	17.4	19.39	19.23
4	17.55	17.28	19.29	19.15
4.5	17.47	17.19	19.26	19.12
5	17.42	17.15	19.3	19.17
5.5	17.45	17.2	19.47	19.34
6	17.55	17.34	19.78	19.65
6.5	17.71	17.53	20.23	20.08
7	17.92	17.75	20.63	20.51
7.5	18.16	18.03	21.09	21.01
8	18.44	18.35	21.6	21.57
8.5	18.76	18.69	22.17	22.18
9	19.1	19.07	22.77	22.81
9.5	19.46	19.45	23.39	23.46
10	19.84	19.86	24	24.11
10.5	20.2	20.29	24.57	24.77
11	20.55	20.74	25.1	25.42
11.5	20.89	21.2	25.58	26.05
12	21.22	21.68	26.02	26.67
12.5	21.56	22.14	26.43	27.24
13	21.91	22.58	26.84	27.76
13.5	22.27	22.98	27.25	28.2
14	22.62	23.34	27.63	28.57
14.5	22.96	23.66	27.98	28.87
15	23.29	23.94	28.3	29.11

Table 13: BMI cutoff points for identifying overweight status and obesity of each gender
Source: Cole et al. (2000)

Note: All the regression discontinuity plots here in the appendix use a third order polynomial on both sides of the cutoff.

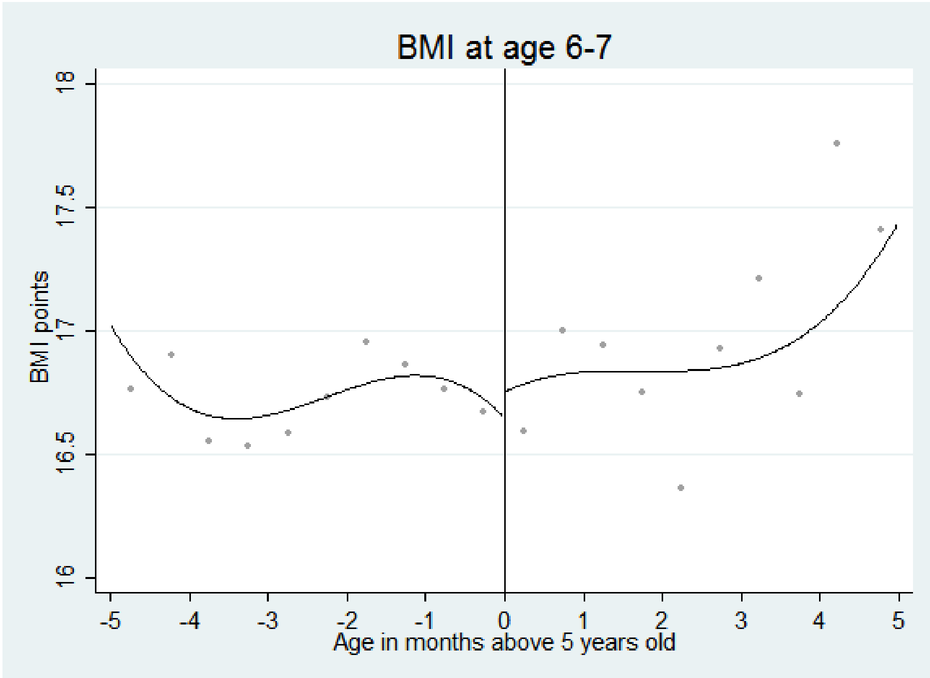

Figure 7: Reduced form plots of BMI at age 6-7

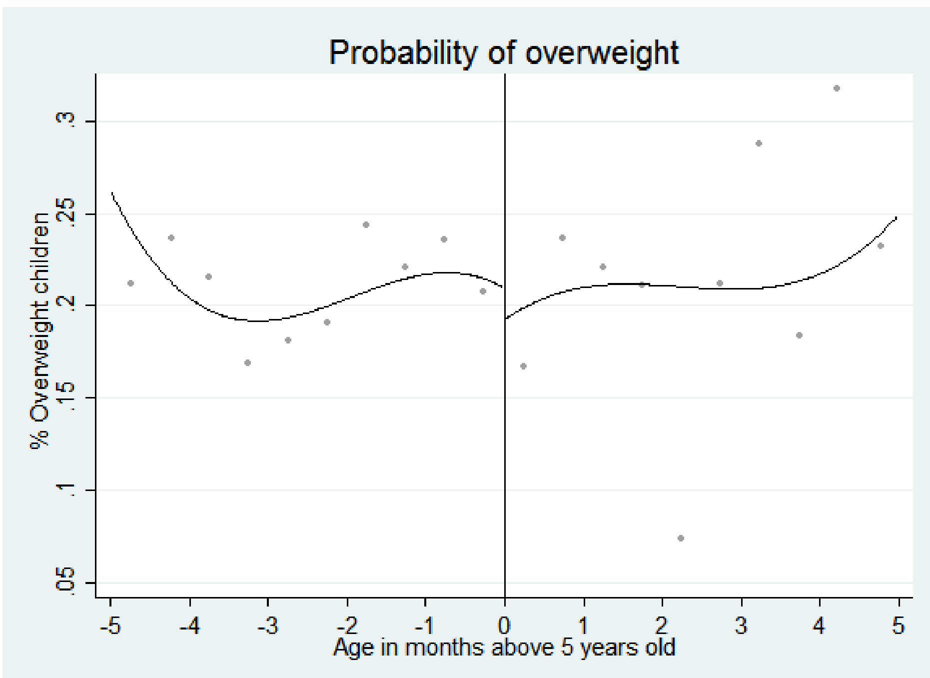

Figure 8: Reduced form plots of overweight status at age 6-7

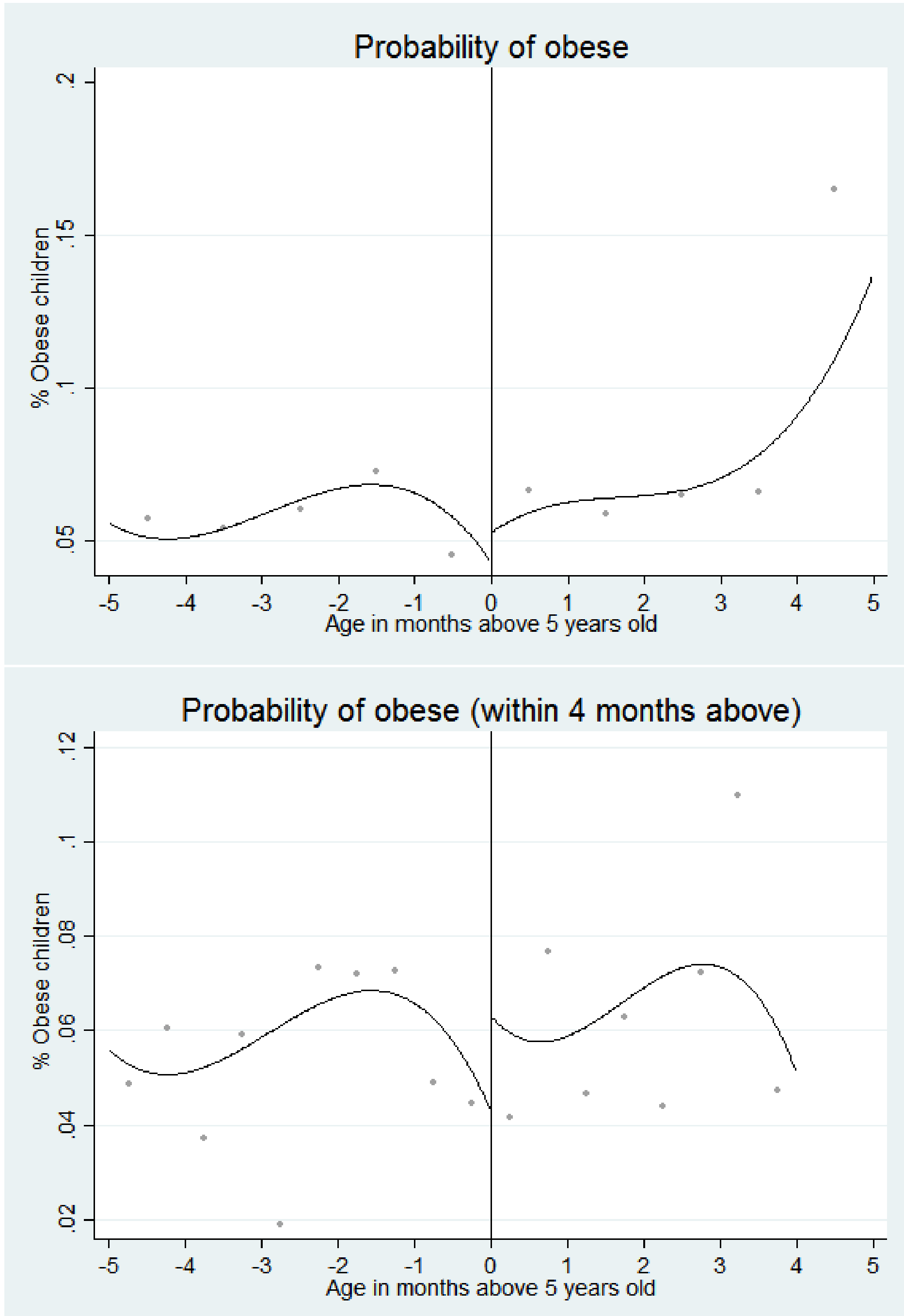

Figure 9: Reduced form plots of obese status at age 6-7

Note: The mean obesity is relatively high at 4-5 months above the cutoff as seen in the first plot, making it difficult to observe the jump in obesity rate at the cutoff. The second plot instead omit the last observation point.

References

ANDERSON, P. M. AND K. F. BUTCHER (2006): "Reading, Writing, and Refreshments Are School Finances Contributing to Children?s Obesity?" *Journal of Human Resources*, 41, 467–494.

ANDERSON, P. M., K. F. BUTCHER, E. U. CASCIO, AND D. W. SCHANZENBACH (2011): "Is being in school better? The impact of school on children's BMI when starting age is endogenous," *Journal of Health Economics*, 30, 977–986.

ANDERSON, P. M., K. F. BUTCHER, AND P. B. LEVINE (2003): "Maternal employment and overweight children," *Journal of health economics*, 22, 477–504.

ANGRIST, J. D. AND V. LAVY (1999): "Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement," *The Quarterly Journal of Economics*, 114, 533–575.

ANGRIST, J. D. AND J.-S. PISCHKE (2008): *Mostly harmless econometrics: An empiricist's companion*, Princeton university press.

ARDZEJEWSKA, K., R. TADROS, AND D. BAXTER (2013): "A descriptive study on the barriers and facilitators to implementation of the NSW (Australia) Healthy School Canteen Strategy," *Health Education Journal*, 72, 136–145.

BAUM, C. F., Y. DONG, A. LEWBEL, T. YANG, ET AL. (2012): "A simple alternative to the linear probability model for binary choice models with endogenous regressors," in *German Stata UsersâĂŹ Group Meetings*, vol. 2.

BEGHIN, J. C. AND H. H. JENSEN (2008): "Farm policies and added sugars in US diets," *Food Policy*, 33, 480–488.

BROWNING, L. M., S. D. HSIEH, AND M. ASHWELL (2010): "A systematic review of waist-to-height ratio as a screening tool for the prediction of cardiovascular disease and diabetes: 0· 5 could be a suitable global boundary value," *Nutrition research reviews*, 23, 247–269.

CAWLEY, J. (2004): "The impact of obesity on wages," *Journal of Human resources*, 39, 451–474.

——— (2010): "The economics of childhood obesity," *Health Affairs*, 29, 364–371.

CAWLEY, J., D. FRISVOLD, AND C. MEYERHOEFER (2013): "The impact of physical education on obesity among elementary school children," *Journal of Health Economics*, 32, 743–755.

CAWLEY, J. AND B. KIRWAN (2011): "Agricultural policy and childhood obesity," .

CAWLEY, J. AND F. LIU (2012): "Maternal employment and childhood obesity: A search for mechanisms in time use data," *Economics & Human Biology*, 10, 352–364.

CAWLEY, J., C. MEYERHOEFER, AND D. NEWHOUSE (2007): "The impact of state physical education requirements on youth physical activity and overweight," *Health economics*, 16, 1287–1301.

CERULLI, G. ET AL. (2012): "ivtreatreg: a new STATA routine for estimating binary treatment models with heterogeneous response to treatment under observable and unobservable selection," *CNR-Ceris Working Papers*.

CHRISTIAN, T. AND I. RASHAD (2009): "Trends in US food prices, 1950–2007," *Economics & Human Biology*, 7, 113–120.

COLE, T. J., M. C. BELLIZZI, K. M. FLEGAL, AND W. H. DIETZ (2000): "Establishing a standard definition for child overweight and obesity worldwide: international survey," *Bmj*, 320, 1240.

COLE, T. J., K. M. FLEGAL, D. NICHOLLS, AND A. A. JACKSON (2007): "Body mass index cut offs to define thinness in children and adolescents: international survey," *Bmj*, 335, 194.

DICKERT-CONLIN, S. AND T. ELDER (2010): "Suburban legend: School cutoff dates and the timing of births," *Economics of Education Review*, 29, 826–841.

EDWARDS, B., M. TAYLOR, AND M. FIORINI (2011): "Who gets the ?gift of time?in Australia? Exploring delayed primary school entry," *Australian Review of Public Affairs*, 10, 41–60.

FERTIG, A., G. GLOMM, AND R. TCHERNIS (2009): "The connection between maternal employment and childhood obesity: Inspecting the mechanisms," *Review of Economics of the Household*, 7, 227–255.

GREENE, W. H. AND D. A. HENSHER (2010): *Modeling ordered choices: A primer*, Cambridge University Press.

GUNDERSEN, C., B. KREIDER, AND J. PEPPER (2012): "The impact of the National School Lunch Program on child health: A nonparametric bounds analysis," *Journal of Econometrics*, 166, 79–91.

HERBST, C. M. AND E. TEKIN (2011): "Child care subsidies and childhood obesity," *Review of Economics of the Household*, 9, 349–378.

IMBENS, G. W. AND T. LEMIEUX (2008): "Regression discontinuity designs: A guide to practice," *Journal of econometrics*, 142, 615–635.

LEE, D. S. AND D. CARD (2008): "Regression discontinuity inference with specification error," *Journal of Econometrics*, 142, 655–674.

LEWBEL, A., Y. DONG, AND T. T. YANG (2012): "Comparing features of convenient estimators for binary choice models with endogenous regressors," *Canadian Journal of Economics/Revue canadienne d'économique*, 45, 809–829.

MADDALA, G. S. (1983): *Limited-dependent and qualitative variables in econometrics*, Cambridge university press.

MILLIMET, D. L., R. TCHERNIS, AND M. HUSAIN (2010): “School nutrition programs and the incidence of childhood obesity,” *Journal of Human Resources*, 45, 640–654.

OGDEN, C. L., K. M. FLEGAL, M. D. CARROLL, AND C. L. JOHNSON (2002): “Prevalence and trends in overweight among US children and adolescents, 1999-2000,” *Jama*, 288, 1728–1732.

SAVVA, S., M. TORNARITIS, M. SAVVA, Y. KOURIDES, A. PANAGI, N. SILIKIOTOU, C. GEORGIOU, A. KAFATOS, ET AL. (2000): “Waist circumference and waist-to-height ratio are better predictors of cardiovascular disease risk factors in children than body mass index,” *International journal of obesity*, 24, 1453–1458.

SCHANZENBACH, D. W. (2009): “Do school lunches contribute to childhood obesity?” *Journal of Human Resources*, 44, 684–709.

SOLUTIONS, A. L. (2006): *Cost/benefit analysis relating to the implementation of a common school starting age and associated nomenclature by 1 January 2010*.

SUZIEDELYTE, A. AND A. ZHU (2015): “Does early schooling narrow outcome gaps for advantaged and disadvantaged children?” *Economics of Education Review*, 45, 76–88.

TARAS, H. AND W. POTTS-DATEMA (2005): “Obesity and student performance at school,” *Journal of School Health*, 75, 291–295.

VON HINKE KESSLER SCHOLDER, S. (2008): “Maternal employment and overweight children: does timing matter?” *Health economics*, 17, 889–906.

WAKE, M. AND B. MAGUIRE (2012): “Children’s body mass index,” *Annual statistical report 2011*, 91.

WOO BAIDAL, J. A. AND E. M. TAVERAS (2014): “Protecting progress against childhood obesity — the National School Lunch Program,” *New England Journal of Medicine*, 371, 1862–1865.

WOOLDRIDGE, J. M. (2010): *Econometric analysis of cross section and panel data*, MIT press.

YAN, W., H. BINGXIAN, Y. HUA, D. JIANGHONG, C. JUN, G. DONGLIANG, Z. YUJIAN, L. LING, G. YANYING, X. KAITI, ET AL. (2007): "Waist-to-height ratio is an accurate and easier index for evaluating obesity in children and adolescents," *Obesity*, 15, 748–752.