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Exploring the causal relation between obesity and alcohol use, and educational outcomes

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EXPLORING THE CAUSAL RELATION BETWEEN OBESITY AND ALCOHOL USE, AND EDUCATIONAL OUTCOMES

Sabine Vuik*, Marion Devaux* and Michele Cecchini*

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- The National Longitudinal Study of Adolescent to Adult Health (Add Health), managed by the Carolina Population Center, University of North Carolina at Chapel Hill, and accessed through the CPC Dataverse (Harris and Udry, 2015[4]) (Harris and Udry, 2015[5]) (Harris and Udry, 2015[6]) (Harris and Udry, 2015[7])[2]
- The Russia Longitudinal Monitoring Survey (RLMS), conducted by the Higher School of Economics and ZAO "Demoscope" together with the Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS, accessed through the CPC Dataverse (Popkin, 2016[8])
- The Christchurch Health and Development Study (CHDS), run by the University of Otago, made available for this study upon request (University of Otago, 2017[9])
- The German Health Interview and Examination Survey for Children and Adolescents (KiGGS), run by The Robert Koch Institute, made available for this study upon request (KiGGS, n.d.[10])
- The Prevention and Incidence of Asthma and Mite Allergy (PIAMA) study, run by the National Institute for Public Health and the Environment (RIVM), the University of Utrecht, the University Medical Centre (UMC) Utrecht, and the UMC Groningen, made available for this study upon request (PIAMA, 2017[11]) (Wijga et al., 2014[12])

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Abstract

Two of the most important health risk factors for children and young adults are obesity and alcohol use. These risk factors are known to affect health and wellbeing, but may also have an impact on educational outcomes. The objective of this study was to assess a potential causal relationship between obesity or alcohol use, and educational outcomes, in Germany, the Netherlands, New Zealand, the Russian Federation, the United Kingdom, and the United States. Longitudinal data from cohort studies was used to establish temporal precedence. To ensure the absence of alternative explanations, regression models were adjusted for known confounders; instrumental variables were used to address endogeneity caused by reverse causality and potential unobserved confounders; and fixed effects analyses were used to correct for unobserved time-invariant confounders. The results suggest that the presence of obesity during childhood, as well as alcohol consumption during childhood, can have a negative impact on educational performance and future educational attainment.

Résumé

L'obésité et la consommation d'alcool sont deux des facteurs de risque les plus importants pour la santé des enfants et des jeunes adultes. On sait que ces facteurs de risque affectent la santé et le bien-être, mais ils peuvent aussi avoir un impact sur les résultats scolaires. L'objectif de cette étude était d'évaluer un lien de causalité potentiel entre l'obésité ou la consommation d'alcool et les résultats scolaires en Allemagne, aux Pays-Bas, en Nouvelle-Zélande, en Fédération de Russie, au Royaume-Uni et aux États-Unis. Les données longitudinales d'études de cohorte ont été utilisées pour établir la hiérarchie temporelle. Pour assurer l'absence d'autres explications, les modèles de régression ont été ajustés par rapport aux facteurs de confusion connus; des variables instrumentales ont été utilisées pour traiter l'endogénéité causée par une causalité inverse et d'éventuels facteurs de confusion non observés; des analyses à effets fixes ont également été utilisées pour corriger les facteurs de confusion invariants non observés dans le temps. Les résultats suggèrent que l'obésité et la consommation d'alcool pendant l'enfance peuvent avoir un impact négatif sur les performances et le futur niveau d'éducation.

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List of acronyms

Add Health	(National Longitudinal Study of) Adolescent to Adult Health
BMI	Body mass index
CHDS	Christchurch Health and Development Study
CI	Confidence interval
EP	Educational performance
EA	Educational attainment
FE	Fixed effects
GPA	Grade point average
IV	Instrumental variables
KiGGS	German Health Interview and Examination Survey for Children and Adolescents
LR	Lagged regression
NS	Not significant
OECD	Organisation for Economic Co-operation and Development
OR	Odds ratio
PIAMA	Prevention and Incidence of Asthma and Mite Allergy study
RLMS	Russia Longitudinal Monitoring Survey
RR	Risk ratio
WHO	World Health Organization

1. Section I – Background of the study

1.1. Introduction

1. Two of the most important behavioural risk factors for children and young adults are obesity and alcohol use. Nearly one in six children are overweight or obese in OECD countries, and rates are predicted to increase even further (OECD, 2017[13]). In addition, young age groups have seen an increase in hazardous drinking and heavy episodic drinking – also called binge drinking (OECD, 2015[14]). These behaviours are associated with a large number of chronic diseases, including diabetes, cancer, cardiovascular disease, liver disease and mental health problems.

2. The OECD work on public health explores the impact of risk factors on the burden of chronic diseases in a population, as well as their consequence for the broader economy (see Box 1.1). This paper falls in the second category: it explores the impact of two risk factors – obesity and alcohol use – on educational outcomes. Educational outcomes are crucially linked to the economy through their impact on the labour market, productivity and innovation. Previous OECD work has explored the effects education has on obesity rates (Sassi et al., 2009[15]), and this paper looks at the reverse relation.

3. Obesity has a wide range of physiological and psychosocial consequences that can affect the performance of students in school. Students with obesity have been shown to have a lower motivation, more detention, and a greater number of absences (Bustillo et al., 2016[16]). Similar effects have been reported for students who use alcohol (Hemphill et al., 2014[17]). In addition, alcohol may also reduce educational outcomes through neurodegeneration and impaired functional brain activity (Balsa, Giuliano and French, 2011[18]). Through these effects, obesity and alcohol use can lead to decreased educational outcomes, and the economic impacts associated with that.

Box 1.1. What does this study add to the OECD work on risk factors?

The Health Division of the OECD Directorate for Employment, Labour and Social Affairs has long worked to understand and quantify the impact of risk factors on public health and the economy. Previous studies have explored the relation between education and obesity (Sassi et al., 2009[19]), or used cross-sectional data to explore the reverse (Devaux, forthcoming).

This study adds to this body of evidence by using longitudinal data to explore a potential causal relationship between obesity, alcohol use and educational outcomes. The use of longitudinal data allows for the exploration of temporal precedence, where the exposure precedes the outcome. In addition, it can be used to adjust for time-invariant confounders.

The results of this study contribute to our understanding of the impact of risk factors on health, society and the economy. In particular, they will be taken into consideration in the future development of the OECD Cost of Illness microsimulation model.

1.2. Aim of this study

4. The aim of this study is to contribute to the body of evidence on the causal relation between obesity and educational outcomes, and alcohol use and educational outcomes. While there are a number of existing studies on these topics, their results are subject to two limitations. Firstly, publication bias may have negatively affected the publication of studies that found no significant effects (Joober et al., 2012[20]). Secondly, discrepancies in variables, study samples and methods limit the cross-country comparability of the existing evidence. This study therefore applies a harmonised, systematic approach to longitudinal data from five OECD countries and the Russian Federation.

5. This study presents different methodological approaches that can be used to identify causal effects. In comparing these methods and discussing their limitations, it aims to provide a comprehensive overview of potential causality.

6. The remainder of this section will present the results from existing longitudinal studies of the impact of obesity on education outcomes; and alcohol use on educational outcomes. Section II will then discuss the methods and data used in this study. Section III presents the results found, and Section IV discusses the implications of these results and the limitations of this study. The Annexes provide additional details on the results, methods and the databases used.

1.3. The complex relationship between obesity, alcohol and educational outcomes

7. The relationship between obesity, alcohol and educational outcomes is multifaceted and complex (see Figure 1.1). There are different pathways in which obesity and alcohol use can impact educational performance; there may be reverse causality; and confounders can impact both the exposure and the outcomes.

8. Obesity and alcohol can have a causal effect on educational outcomes through biological, behavioural, and emotional or mental health factors. Firstly, alcohol use, obesity

and their related diseases (such as the metabolic syndrome) may have a direct biological effect on cognitive functions and concentration at school:

- There is evidence for a causal effect of metabolic syndrome on cognitive functions and brain structure through physiological impairments (Yates et al., 2012[21]).
- Another study found a direct link between childhood obesity and lower cognitive performance, independently of physical activity, sleep, and diet (Hjorth et al., 2016[22]).
- Alcohol has been shown to cause neurodegeneration and impaired functional brain activity (Balsa, Giuliano and French, 2011[18]).

9. Secondly, obesity and alcohol use can also lead to behavioural changes that affect educational performance:

- Obesity may decrease the amount of physical activity that children undertake, resulting in lower concentration (Bustillo et al., 2016[16]).
- Alcohol use has been shown to be associated with absenteeism from school (Holtes et al., 2015[23]).

10. Thirdly, emotional or mental health factors related to obesity and alcohol use can also affect educational performance:

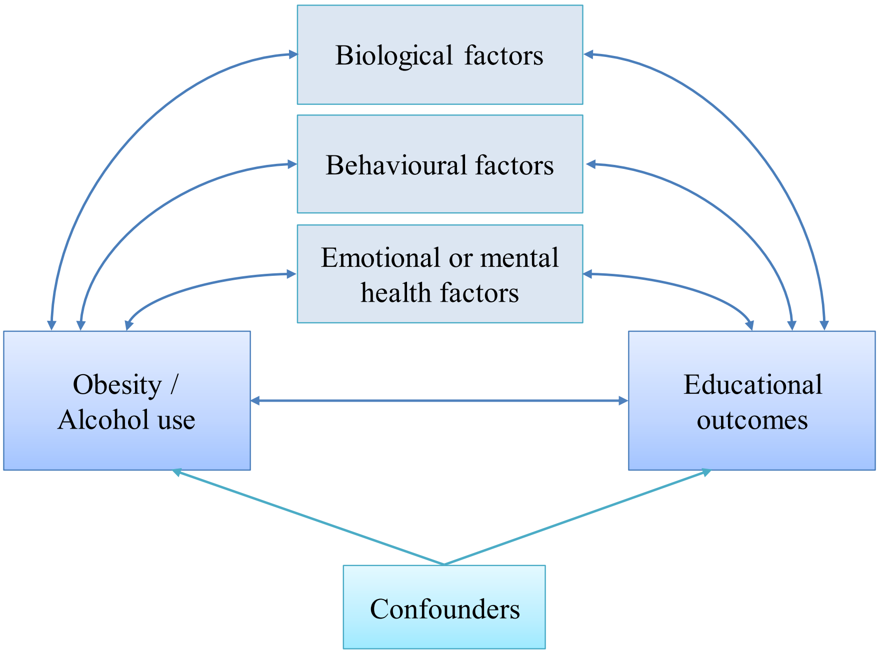
- Bullying, lower self-esteem and poor social connections are associated with obesity in children, and can have an impact on educational performance (Russell-Mayhew et al., 2012[24]) (Strauss, 2000[25]).
- Alcohol use can negatively affect relationships with other students and teachers and commitment to school work (Hemphill et al., 2014[17]).

11. However, inverse relationships also exist. For example:

- Students who do less well in school may be more likely to engage in binge drinking as a coping mechanism (Donath et al., 2012[26]), and the same may apply to overeating leading to obesity.
- Education also provides students with access to health-related information and a clearer understanding of the impact of lifestyle choices (Devaux et al., 2011[27]).

12. In addition, there exist a wide range of confounding factors that influence both the risk factors and the outcome, such as family income, parental education, self-esteem and motivation.

Figure 1.1. Relation between obesity, alcohol use and educational outcomes



1.4. Existing longitudinal studies of obesity and educational outcomes

13. Longitudinal data can be used to establish a temporal relationship. While there exist a large number of cross-sectional studies exploring the relation between obesity and educational outcomes (e.g. (Carey et al., 2015[28]) (Anderson and Good, 2017[29]) (Torrijos-Niño et al., 2014[30]) (Li et al., 2012[31]) (Pan et al., 2013[32])), there are fewer studies that use longitudinal data. These studies have found varying results.

14. A number of studies have found a temporal association between obesity and educational outcomes:

- Using a retrospective cohort study, Adaili et al. explored the relation between overweight and obesity and future academic performance among female high school students (Adaili, Mohamed and Alkhashan, 2017[33]). They found that girls who were overweight or obese in 10th grade had 3.73 higher odds to experience a decline in grades between the 10th and 12th grade than normal weight students.
- Karnehed et al. looked at the impact of obesity on educational attainment in Swedish men (Karnehed et al., 2006[34]). They found that men who were obese at age 18 had 70% less chance of completing at least 15 years of education than normal-weight subjects, even when adjusting for intelligence and socio-economic factors.

15. Other studies, looking at younger children, found no relation between obesity and educational outcomes.

- Ruijsbroek et al. analysed the relationship between common childhood health conditions and educational performance at the end of primary school, using the

Dutch PIAMA birth cohort study (Ruijsbroek et al., 2015[35]). They found no significant relation between the number of years that the child was overweight and final year test scores or teacher assessment.

- Similarly, a study following elementary school children over 6 years found that BMI changes were not significantly associated with changes in academic performance (Chen et al., 2012[36]).
- Viner and Cole looked at the relation between obesity at 10 years old and educational attainment at 30 years old using the 1970 British Cohort Study, and found no statistically significant relation after adjusting for confounders such as social class, parental BMI and education (Viner and Cole, 2005[37]).

16. Some studies found different results for male and females:

- Booth et al. used the UK-based ALSPAC cohort to explore the impact of overweight and obesity on future test scores (Booth et al., 2014[38]). They found that being obese at age 11 decreased the English marks of girls by 0.082 and 0.072 points at age 13 and 16 respectively, compared to girls with a healthy weight, even after controlling for confounders. However, the effect was not significant for boys.
- Datar and Sturm similarly found different results for boys and girls (Datar and Sturm, 2006[39]). Using the United States ECLS-K study of kindergartners, they measured the impact of changes in overweight status on mathematics and reading assessments between kindergarten entry and third grade. While becoming overweight decreased mathematics scores by 1.62 and reading scores by 2.54 in girls, a similar effect was not found for boys.

1.5. Existing longitudinal studies of alcohol use and educational outcomes

17. Similar to the evidence on obesity and education, the existing body of literature regarding the relation between alcohol and educational outcomes is based mostly on cross-sectional studies (e.g. (DeSimone and Wolaver, 2006[40]) (El Ansari, Stock and Mills, 2013[41]) (Sung, So and Jeong, 2016[42]) (Holtes et al., 2015[23])). The studies using longitudinal data present mixed findings.

18. Some studies found evidence of a temporal relation between alcohol consumption and educational outcomes:

- Hemphill et al. looked at the effect of early adolescent alcohol use on mid-adolescent school suspension, truancy, commitment, and academic failure in the United States and Australia (Hemphill et al., 2014[17]). They found that grade 7 alcohol use and binge drinking was associated with grade 8 suspension and grade 9 truancy (for example, students who used alcohol in grade 7 had 68% higher odds of being suspended). However, there was no significant effect on academic achievement and school commitment.
- Using data from the longitudinal Brain and Alcohol Research in College Students study, Meda et al. looked at the impact of alcohol and marijuana use on United States students' grade point average (GPA) (Meda et al., 2017[43]). They showed that students using moderate to high levels of alcohol but low marijuana had lower GPAs, but this difference became non-significant over time. However, students using both substances had lower GPAs throughout the study period.

19. Other studies found no significant effect of alcohol use on educational outcomes:

- A study using the Add Health cohort looked at the effects of binge drinking on GPA, and found no statistically significant relation between the two (Sabia, 2010[44]).
- Silins et al. used three Australasian longitudinal cohorts to explore the relation between adolescent alcohol use and educational attainment by age 25 (Silins et al., 2015[45]). They found weak and statistically insignificant relations between frequency of alcohol use and non-attainment of secondary school and tertiary qualifications after adjustment for confounders.
- Chatterji used two different methods to estimate the association between high school alcohol use and educational attainment at 26 in the United States National Education Longitudinal Study (Chatterji, 2006[46]). While ordinary regression indicated that the two are correlated, the results from a constrained bivariate probit model (which takes into account a potential association caused by common, unmeasured determinants) suggest that alcohol use had no causal effect on educational attainment, despite the strong association between the variables.

20. As with obesity, differences between males and females were found:

- Balsa et al. used the Add Health cohort to link alcohol consumption to GPA in a fixed effects model (Balsa, Giuliano and French, 2011[18]). While alcohol consumption results in a small but statistically significant reduction in GPA for boys (0.07 points per 100 drinks per month), for girls this effect was not significant.

2. Section II – Data and methods

2.1. Data sources

21. The objective of this study was to assess a potential causal relationship between obesity or alcohol use, and educational outcomes. To be able to establish causality, longitudinal data was used. Longitudinal or panel data contains repeated measures on the same cohort of individuals over time (Gunasekara et al., 2014[47]). Longitudinal data can therefore be used to establish temporal precedence – where the cause precedes the outcome. Together with covariation and the absence of alternative explanations, a temporal relation is an important indicator of causality (Oppewal, 2010[48]).

22. The results in this paper are based on data from longitudinal cohort studies in the United Kingdom (the 1970 British Cohort Study), the United States (the National Longitudinal Study of Adolescent to Adult Health, or Add Health), the Russian Federation (Russia Longitudinal Monitoring Survey, or RLMS), New Zealand (Christchurch Health and Development Study, or CHDS), Germany (The German Health Interview and Examination Survey for Children and Adolescents, or KiGGS) and the Netherlands (The Prevention and Incidence of Asthma and Mite Allergy, or PIAMA). Details on these cohorts are reported below and in Annex V. These cohorts were selected as they included school-aged children and collected data on obesity or alcohol use, and educational performance or attainment.

Box 2.1. Overview of the cohort studies used in this paper

Please note that this box provides a high-level overview. Additional details on the data used in this paper, including descriptions of the cohort studies, sample sizes and characteristics, variable definitions, missing data and descriptive statistics can be found in Annex V

Country	Name of the survey	Data used
Unites States	The Add Health cohort	EP: Age 12-21 (1994-5) & Age 13-22 (1996); n=4,832 EA: Age 12-21 (1994-5) & Age 25-34 (2008); n=5,114
United Kingdom	The 1970 British Cohort Study	EA: Age 16 (1986) & Age 29/30 (1999/2000); n=8,328
Russian Federation	The Russia Longitudinal Monitoring Survey	EP: Age 5-13 (2010-2015); n=10,012 EA: Age 16/17 (1994-2003) & Age 29/39 (2006-15); n=717
New Zealand	The Christchurch Health and Development Study	EP: Age 16 (1993) & Age 18 (1995); n=926 EA: Age 16 (1993) & Age 25/35 (2002/2012); n=922
Germany	The KiGGs study	EP: Age 1-11 (2003-2006) & Age 8-17 (2009-2012); n=6,777 for lagged regression; n=2,302 for fixed effects
Netherlands	The PIAMA study	EP: Age 11 (2007-8) & Age 17 (2013-2014); n=1,892

EP: Educational performance; EA: Educational attainment

The Add Health cohort (United States)

The analysis for the United States is based on data from the National Longitudinal Study of Adolescent to Adult Health (Add Health). This longitudinal study started with a nationally representative sample of United States adolescents in grades 7 through 12 during the 1994-1995 school year. This cohort was followed into young adulthood through four in-home interviews, the most recent one conducted in 2008 when the sample was aged 25-34.

For the educational performance analysis, Wave 1 and Wave 2 were used, which were conducted one year apart in 1994-95 and 1996 respectively. This sample consists of 4,832 complete observations for students from Wave 1 who also participated in Wave 2. For the educational attainment analysis Wave 4 was used, with Waves 1 as predictors. For this analysis, the 5,114 students who participated in both Waves 1 and 4 were used.

The 1970 British Cohort Study (United Kingdom)

The 1970 British Cohort Study follows the lives of more than 17,000 people born in England, Scotland and Wales in a single week of 1970. Subsequently, data was collected at 5 to 10 years intervals, including at ages 5, 10, 16, 26, 29/30; with the latest in 2016 at age 46.

Due to the high rate of missing data on performance at age 16, this analyses could not be conducted. For the educational attainment study, the wave at 16 years old was compared to outcomes at 29 years old: 8,328 students participated in both these two waves.

The Russia Longitudinal Monitoring Survey (Russian Federation)

The Russia Longitudinal Monitoring Survey (RLMS) has collected data annually since 1992, providing reliable data on a nationally representative sample from 1994 onwards. The most recent year available was 2015. While the survey is not focused on children, they are included as part of the households that make up the sample.

Since educational performance was only measured from 2010 onwards, and only in children under the age of 14, the sample for this analysis was based on these restrictions:

children who were in school at any time between 2010 and 2015 and under the age of 14, resulting in 10,012 observations over 6 years, with between 1,482 and 1,803 students per year.

For the educational attainment analysis, participants were selected if their alcohol use was recorded at age 16 or 17, and if this occurred before 2003 to allow a follow-up at age 29/30 within the timeframe of the study. This resulted in a sample of 717 people.

The Christchurch Health and Development Study (New Zealand)

The Christchurch Health and Development Study (CHDS) follows a cohort of 1,265 children born in the New Zealand city of Christchurch in 1977. A total of 953 people participated at age 16 (which was used as the exposure year), and were included in the sample for this study. At 18, a standardised reading score was calculated, which was used to measure educational performance. At 25 years, the age at which the participant left full-time education was calculated. At 35 years, the highest educational qualification obtained was recorded.

While alcohol use at age 16 was available, no data was collected on weight and height or on obesity status. The New Zealand data was therefore used only to explore the effects of alcohol on educational outcomes.

The KiGGs study (Germany)

The first wave of the KiGGS study was conducted between 2003 and 2006. This baseline study collected comprehensive health data on a nationally-representative sample of children and adolescents. Data for the first follow-up wave (KiGGS1) was collected between June 2009 and June 2012. The second follow-up, KiGGS2, took place between 2014 and 2017, but the data was not yet available at the time of this study.

The baseline study included 17,640 children between the ages of 0 and 17. The follow-up took place 3 to 9 years later, at which point the majority of participants were not old enough yet to establish educational attainment. Educational performance was measured based on average grades. Questions on alcohol use and smoking habits were asked only of children aged 11 and over. As these children were 17 and over in the follow-up study, they did not obtain grades anymore. As a result, the German data was used only to explore the impact of obesity on educational performance.

The PIAMA study (the Netherlands)

The primary aim of the PIAMA study was to research the impact of risk factors on the development of asthma and mite allergy during the first 8 years of childhood in 4,000 children born in 1996 or 1997. After this time point, follow-up was continued at 11, 14 and 17 years old, to study longer term effects as well as other chronic diseases. These last 3 waves were considered for this study.

Academic performance was measured as the school level attended between 11 and 17 years old, and the exposures were therefore taken at 11 years old. It was impossible to determine whether the exposures recorded at 14 years old preceded the educational outcomes, and they could therefore not be used to study a temporal, causal relation. The follow-up time was not long enough to measure academic attainment. Similarly, alcohol use at 11 years old was minimal, and could not be used as exposure.

2.2. Variables

23. Educational outcomes were measured as educational performance and educational attainment.

24. **Educational performance** is the performance of a student during his or her time in education. Educational performance may change over time and can therefore be compared at different time points. This includes, for example:

- Grades obtained in school subjects
- Teacher's assessment of performance relative to other students
- Tests scores

25. **Educational attainment** is the level of education ultimately achieved. Contrary to educational performance, this cannot be measured over time as it is a final outcome. This includes, for example:

- Highest degree obtained
- Number of years spent in full-time education (or age at which they left full-time education)
- Whether the student completed any (degree-level) higher education

26. To determine overweight and obesity from BMI values, the World Health Organization childhood obesity cut-off values were used (see Table 2.1).

Table 2.1. Childhood obesity and overweight BMI cut-offs

Age	Girl – Obesity	Girl - Overweight	Boy - Obesity	Boy - Overweight
5	18.8	16.8	18.3	16.6
6	19.2	17.0	18.5	16.8
7	19.8	17.3	19.0	17.0
8	20.6	17.7	19.7	17.4
9	21.5	18.3	20.5	17.9
10	22.6	19.0	21.4	18.5
11	23.7	19.9	22.5	19.2
12	25.0	20.8	23.6	19.9
13	26.2	21.8	24.8	20.8
14	27.3	22.7	25.9	21.8
15	28.2	23.5	27.0	22.8
16	28.9	24.1	27.9	23.5
17	29.3	24.5	28.6	24.3
18+	30	25	30	25

Source: World Health Organization and (de Onis et al., 2007[49])

27. An effort was made to standardise the analyses across the different country datasets. However, due to differences in the collected and reported data, different variables and concepts were used per country (see Table 2.2). While height and weight were measured during a physical examination in some cohorts, in others they were self-reported. Alcohol use was also reported differently in the various datasets. To correct for socio-economic status, different variables were used depending on the availability of data.

Countries collected different data on educational performance, including grades, reading test scores, and teachers' assessment of performance.

Table 2.2. Overview of variables included in the analyses

	United States	United Kingdom	Russia	New Zealand	Germany	Netherlands
Educational performance	Grade point average or GPA (cont)	N/A	Average grade obtained (cont)	BURT reading score (cont)	Average grade (mathematics & german) (cont)	Level of high school (bin); High school level below assessment (bin)
Educational attainment	Completed any higher education (bin)	Completed any higher education (bin); Age left FT education (cont)	Completed any higher education (bin)	Completed any higher education (bin); Age left FT education (cont)	N/A	N/A
Obesity	Obesity status (cat: obese; overweight; normal weight); BMI (cont) [Self-reported]	Obesity status (cat: obese; overweight; normal weight); BMI (cont) [Measured]	Obesity status (cat: obese; overweight; normal weight); BMI (cont) [Self-reported]	N/A	Obesity status (cat: obese; overweight; normal weight); BMI (cont) [Measured]	Obesity status (cat: obese; overweight; normal weight); BMI (cont) [Parent-reported]
Alcohol use	Frequency drinking (cat: rarely; monthly; weekly); Units drunk per month (cont); Frequency binging (cat: rarely; monthly; weekly)	Frequency drinking (cat: rarely; monthly; weekly); Units drunk last week (cont); Frequency binging last 2 weeks (cat: none; once; more than once)	Frequency drinking (cat: rarely; monthly; weekly)	Frequency drinking (cat: rarely; monthly; weekly); Any binge drinking in last 3 months (bin)	N/A	N/A
Socio-economic status	Annual income (cat: 5 quintiles)	Weekly income (cat: 5 quintiles); Social class father (cat: partly or unskilled; manual or non-manual; managerial or professional)	Monthly household income (cat: 5 quintiles); Economic rank (cat: 3 groups, based on predefined ranks)	Average household income (cat: 5 quintiles); Social class father (cat: partly or unskilled; manual or non-manual; managerial or professional)	Socio-economic rank (cat: 5 quintiles of predefined SES scores);	Education mother (cat: low; intermediate; high); Education father (cat: low; intermediate; high)
Ethnicity/ minority/ immigration status	Ethnicity (cat: Latino/Hispanic; other minority; other white)	Minority (bin)	Russian (bin)	Maori/Pacific Islander (bin)	Immigrant (bin)	Minority (bin)
Age	Age (cont)	N/A	Age (cont)	Age (cont)	Age (cont)	Age (cont)
Sex	Sex (bin)	Sex (bin)	Sex (bin)	Sex (bin)	Sex (bin)	Sex (bin)

	United States	United Kingdom	Russia	New Zealand	Germany	Netherlands
Smoking	N/A	Smoker (bin)	Smoker (bin)	Smoker (bin)	N/A	N/A
IV obesity	N/A	BMI mother (cont); BMI father (cont)	N/A	N/A	BMI mother (cont); BMI father (cont)	BMI mother (cont); BMI father (cont)
IV alcohol	How many out of 3 best friends drink (cont);	Who drinks out of older sister, brother, boyfriend or girlfriend, best friend, next best friend (as # and %*, both cont)	N/A	How many of your friends use alcohol at age 15 (cat: none; some; most); How many of your friends use alcohol at age 16 (cat: none; some; most)	N/A	

Notes: cont: continuous; bin: binary; cat: categorical; N/A: not applicable; FT: full-time. * the four variables were combined into an absolute number and a percentage, to account for cases where respondents did not have a brother, sister, boyfriend etc. For more details on the variables, please see Annex V.

2.3. Methods

28. This study aims to identify a potential causal relationship between the risk factors and educational outcomes. To establish causality, three criteria need to be met (Oppewal, 2010[48]):

1. Covariation
2. Temporal precedence
3. Absence of alternative explanations

29. Regression models were used to determine whether there was *covariation* between the exposure (obesity or alcohol use) and the outcome (educational performance or attainment). To establish whether there is *temporal precedence*, the risk factors were lagged. This means that the risk factor status (i.e. obesity or alcohol consumption) was taken from a data collection wave preceding the one in which the outcome was measured. To ensure the absence of *alternative explanations*, the models were adjusted for known confounders, such as socio-economic status, gender, age and ethnicity. In addition, instrumental variables were used to address endogeneity caused by reverse causality and potential unobserved confounders, and fixed effects analyses were used to correct for unobserved time-invariant confounders. For details on these econometric methods, and how they were used in this study, please see Annex IV.

30. Instrumental variables are widely used to address unobserved effects, yet the difficulty of finding appropriate instruments – and the impact that inappropriate instruments have on the results – means that IV models can sometimes do more harm than good (Crown, Henk and Vanness, 2011[50]). This study therefore presents the results of both non-instrumented, lagged regression models and their instrumented versions. It also explores the endogeneity that is present in the non-instrumented models, to identify whether IV models are necessary, and tests the strength of the instruments.

31. Where possible, the results were presented as linear regression coefficients for continuous outcomes and risk ratios or relative risks (RRs) for binary outcomes. Linear regression coefficients represent the unit change in the outcome due to a unit change in the exposure. RRs measure the risk of an outcome in the exposure group relative to the risk in the non-exposed group, with a value of one being equal risk.

32. However, in some cases the models producing RRs would not converge, and other methods producing odds ratios (ORs) had to be used. Odds ratios do not take into account the prevalence of the exposure in the population, but are similar to RRs in that a value larger than one represents greater odds or risk, and lower than one lower odds or risk.

33. While this mix of outcome measures complicates the reporting of the results, RRs were chosen over OR as they are more intuitive to interpret. Moreover, ORs can overestimate and magnify risk when the outcome is more common (Last, 2004[51]). A benefit of ORs is that they do not take into account the prevalence of the exposure, and can therefore be useful when rates are compared across groups or countries with different exposure rates. However, in this study the variables, follow-up time and population characteristics vary greatly across countries, and the effect sizes will therefore not be compared either way.

34. For the IV models with a binary outcome only probit coefficients could be produced. Probit coefficients represent the change in the z-score of the outcome for every unit change in the exposure. While methods exist to convert this to marginal changes in the outcome, these did not work with the models used in this study. However, probit coefficients are similar to linear regression coefficient in that a positive value represents an increase in the probability of the outcome, and a negative value a decrease.

35. The models were adjusted for the following confounders: age, ethnicity/minority/immigration status, socio-economic class (e.g. income, socioeconomic ranking, parental education or profession), and smoking. The analyses looking at the impact of obesity were corrected for alcohol use and vice versa, where the data allowed.

36. Previous research has shown that boys and girls are different in terms of alcohol use, alcohol metabolism, body size and educational achievements (Devaux and Sassi, 2015[52]). Analyses on these topics are therefore often conducted separately for males and females (Gable, Krull and Chang, 2012[53]) (Booth et al., 2014[38]) (Balsa, Giuliano and French, 2011[18]) (Staff et al., 2008[54]) (Datar and Sturm, 2006[39]). This approach was also adopted in this study.

37. Another approach would have been to include an interaction term between gender and obesity or alcohol use. This would have increased the sample size of the analysis, as well as providing a statistical comparison of the effect in boys and girls. However, there is reason to assume that the educational effects of other factors in the model – such as socio-economic class, income and minority status – also differ by gender (OECD, 2015[55]). Including interaction terms for all variables would have complicated the convergence and interpretation of the models, and analyses were therefore conducted separately for boys and girls.

3. Section III – Results

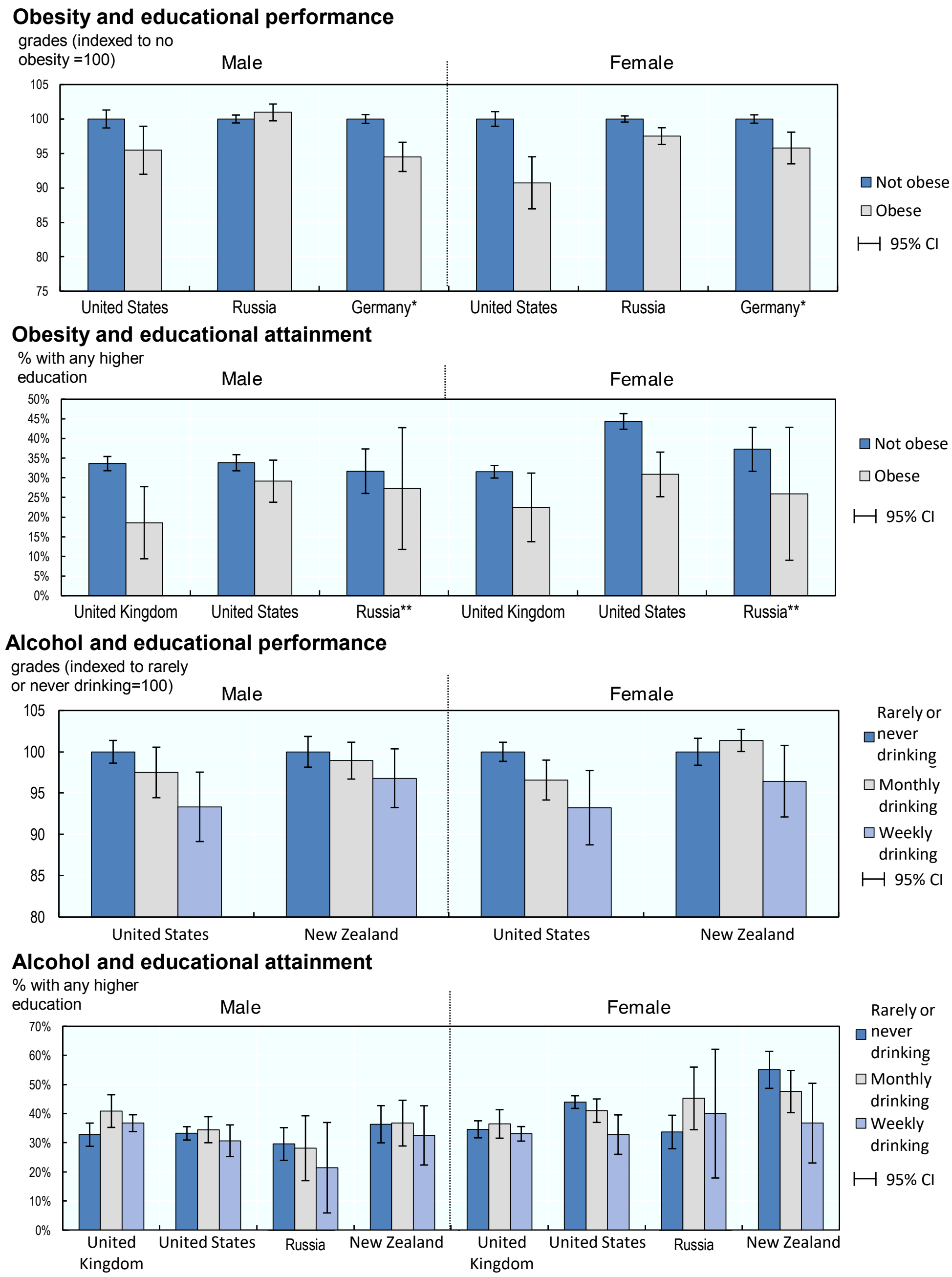
38. This section presents the results of the analyses. The first part shows the unadjusted correlations between the risk factors and educational outcomes. The second part focuses on obesity and educational outcomes, and presents the results from the lagged models as well as any fixed effects or instrumental variable analyses that were run. The third part presents the same results for alcohol use and educational outcomes. Detailed results of the analyses are available in Annex I.

3.1. Unadjusted lagged models

39. At a high level, a one-directional relation between obesity and educational performance was found (see Figure 3.1 and Annex II for details). Students with obesity generally achieved lower grades later on in their school career (with the exception of men in Russia – though this effect was not statistically significant). A similar relation was observed in all countries between obesity and attaining any higher education: students who were obese during their school years were less likely to complete higher education. However, in some cases the differences were insignificant, especially where the sample size of the obese group was small.

40. The unadjusted relation between alcohol use and educational outcomes was less straightforward. In most countries, there was an overall trend showing that drinking more was associated with lower grades. However, in some cases drinking monthly was associated with an increased likelihood of completing higher education compared to weekly and rarely drinking. Moreover, for men in the United Kingdom and women in Russia even weekly drinking was associated with an increased likelihood of completing higher education compared to not drinking in school. As with obesity, small sample sizes (in particular for Russia) meant that it cannot be ruled out that some of these difference are due to chance.

Figure 3.1. Unadjusted lagged relations between obesity, alcohol use and educational outcomes



Note: All exposures are lagged to the educational outcomes, e.g. obesity was measured in wave t-1 and compared to grades in wave t=0. As grades were measured according to different scales in the various countries, all were indexed to set the average grade of the "no obesity" and "rarely drinking" groups to 100. Grades for the other groups were rescaled accordingly: a value of 90 represent a 10% lower grade while a value of 110 is a 10% higher grade. See Annex II for details.

* Grades in Germany are shown inverted so that a lower number equals a lower performance

** For Russia, obesity and overweight were combined in the educational attainment sample due to the low prevalence of obesity

3.2. Relation between obesity and educational outcomes

Table 3.1. Relation between BMI and educational outcomes

	United States	United Kingdom	Russia	Germany	Netherlands
Educational performance					
Male	**Negative impact** (LR) Not significant (FE)		**Positive impact** (LR) Not significant (FE)	Not significant (LR) **Negative impact** (FE) **Negative impact** (IV)	**Negative impact** (LR) Not significant (IV)
Female	**Negative impact** (LR) Not significant (FE)		**Negative impact** (LR) Not significant (FE)	Not significant (LR) Not significant (FE) Not significant (IV)	Not significant (LR) Not significant (IV)
Educational attainment					
Male	Not significant (LR)	**Negative impact** (LR) Weak IVs (IV) **Negative impact** (IV)*	Not significant (LR)		
Female	**Negative impact** (LR)	Not significant (LR) **Negative impact** (LR)* **Negative impact** (IV)	Not significant (LR)		

Note: LR: Lagged regression; IV: Instrumental variable analysis; FE: Fixed effects analysis; all adjusted for confounders. Presenting only results of analyses using BMI as exposure, and using “any higher education” as outcome for educational attainment (or “age when left full-time education” where the results were different, marked *). Significance level set at 0.05. For more results, please see Annex I

3.2.1. Overall, a negative relation was observed between obesity and educational performance

41. In the United States study population, there was a statistically significant relation between BMI or obesity in Wave 1 and GPA in Wave 2, even when correcting for confounders such as age, gender, family income and ethnicity (note that all results presented here are adjusted for confounders unless otherwise specified) (see Table 3.1 for an overview, and Annex I for detailed results). The GPA of girls with obesity was 0.26 points lower than those of girls with normal weight. This equates to a student with a median GPA of 2.75 dropping to the 45th percentile. Similarly, a point increase in BMI was associated with 0.009 points (95% CI: 0.0001 to 0.0178) decrease in GPA for boys; and 0.021 points (95% CI: 0.015 to 0.028) for girls. The effect of one BMI point change was small, as the average GPA for girls, of 2.95, had a standard deviation of 0.74. When using a fixed effects model the effect was no longer significant.

42. In the Russian sample BMI was also associated with lower grades for girls, by 0.007 (0.002 to 0.012) points per point BMI. Again, this effect was small as compared to a standard deviation of 0.50. There also was a significant effect of BMI on grades for boys, but the effect was in the opposite direction: a one-point increase in BMI was linked to a 0.007 (0.001 to 0.012) point increase in average grade. However, as in the United States dataset, fixed effects models – both direct and with a one-year lag – found no significant effect for either sex.

43. In the Netherlands, boys who were obese or overweight at age 11 were 20% less likely to attend a higher level of high school (RR: 0.80, 0.65 to 0.95), while the effect for girls was not significant. However, when looking at performance relative to the teacher’s assessment at age 11, there was no significant effect of obesity, overweight or BMI in either sex. The instrumental variable model did not find a significant effect. However, no

endogeneity was observed in the non-instrumented model, meaning that the original model may be preferred.

44. In Germany, no significant relation was found between obesity and educational performance in either sex using a lagged regression. However, a fixed effects model found a significant negative relation between BMI and grades in boys. For every point increase in BMI, grades (scaled 1 to 6, with 1 being the highest grade) increased by 0.040 (0.002 to 0.077) – indicating a lower performance in school. The effect was small as compared to the standard deviation, which was 0.80. For girls a similar effect was found, but this was only significant at the 0.10 level.

45. When using instrumental variables (BMI of the mother and of the father), the effect persisted in the Germany database. Grades for boys were 0.08 (0.01 to 0.14) points higher in the follow-up for every point of BMI in the baseline measurement (with higher grades indicating a lower performance). In addition, the tests showed that the instrumental variables were strong, and that there was evidence of endogeneity in the non-instrumented model. Again, there was a similar effect for girls but at a lower significance level.

3.2.2. Obesity appeared to have a negative impact on educational attainment in the United Kingdom and the United States

46. While neither obesity nor BMI in Wave 1 predicted whether a boy would complete higher education in the US, both variables were significant predictors for girls. A girl who was obese in Wave 1 was 38% less likely to complete higher education than someone of normal weight (RR: 0.72, 0.59 to 0.88).

47. Conversely, in the United Kingdom, the relation between obesity and educational attainment was significant only for boys, who were 58% less likely to complete higher education if they were obese at age 16 (RR: 0.42, 0.16 to 0.95). However, a higher BMI did have a significant effect in girls: for each point increase in BMI at age 16 girls spent 0.044 (0.004 to 0.085) years less in higher education.

48. When using instrumental variables for BMI (namely BMI of the mother and of the father) in the United Kingdom dataset, the negative effect of BMI on completing higher education remained significant for boys and became significant for girls. However, for boys the instrumental variables were weak. In addition, a significant effect was found for both genders when using an IV model to look at the age they left education: each point increase in BMI was associated with leaving full-time education 0.20 (0.001 to 0.40) years earlier for boys, and 0.23 (0.09 to 0.37) years earlier for girls. For both sexes the instruments were strong and there was evidence of endogeneity.

49. In Russia no significant relation was found between obesity and educational attainment using lagged regression models.

3.3. Relation between alcohol use and educational outcomes

Table 3.2. Relation between alcohol use frequency and educational outcomes

	United States	United Kingdom	Russia	New Zealand
Educational performance				
Weekly alcohol use				
Male	**Negative impact** (LR) Not significant (FE) **Negative impact** (IV)			Not significant (LR) Not significant (IV))
Female	**Negative impact** (LR) Not significant (FE) **Negative impact** (IV)			Not significant (LR) Not significant (IV)
Frequent binge drinking				
Male	**Negative impact** (LR) **Negative impact** (IV)			Not significant (LR) Not significant (IV))
Female	**Negative impact** (LR) **Negative impact** (IV)			Not significant (LR) Weak IV (IV)
Educational attainment				
Weekly alcohol use				
Male	Not significant (LR) Not significant (IV)	Not significant (LR) Not significant (IV)	Not significant (LR)	Not significant (LR) **Negative impact** (LR)* Not significant (IV)
Female	**Negative impact** (LR) **Negative impact** (IV)	Not significant (LR) **Negative impact** (LR)* Not significant (IV) **Negative impact** (IV)*	Not significant (LR)	Not significant (LR) Not significant (IV)
Frequent binge drinking				
Male	Not significant (LR) Not significant (IV)	Not significant (LR) **Negative impact** (LR)* Not significant (IV)		Not significant (LR) Not significant (IV)
Female	**Negative impact** (LR) **Negative impact** (IV)	Not significant (LR) **Negative impact** (LR)* Not significant (IV) **Negative impact** (IV)*		Not significant (LR) Not significant (IV)

Note: LR: Lagged regression; IV: Instrumental variable analysis; FE: Fixed effects analysis; all adjusted for confounders. Presenting only results of analyses using weekly alcohol consumption or the most frequent binge drinking category as exposure and using "any higher education" as outcome for educational attainment (or "age when left full-time education" where the results were different, marked *). Significance level set at 0.05. For more results, please see Annex I

3.3.1. Frequent alcohol use was negatively associated with educational performance in the United States, but in New Zealand no significant effects were found

50. In the United States, a significant relation between alcohol use and educational performance was found (see Table 3.2). Monthly and weekly drinking was associated with a decrease in GPA of 0.11 and 0.19 points respectively for boys, and 0.11 and 0.20 points in girls, compared to those who rarely or never drank. Binge drinking had an even greater association with GPA, as weekly binge drinking was linked to a reduction in the GPA of boys (0.25 points, 0.10 to 0.40) and girls (0.21 points, 0.02 to 0.39). A reduction of 0.25 points would bring a student with the median GPA of 2.75 down to the 40^{th} percentile.

51. There was strong evidence of endogeneity in the models for both boys and girls in the United States, indicating that an IV approach might be preferred over traditional

regression. The IV models also found a significant negative relation between weekly alcohol use or binge drinking and educational performance, but with a much larger effect size: weekly binge drinking was associated with a decrease in GPA of 1.57 (0.92 to 2.22) points in boys and 2.36 (1.31 to 3.42) points in girls, compared to those who did not binge drink weekly.

52. These effect sizes must be interpreted with caution. IV models are known to be less precise and produce larger standard errors (Pokropek, 2016[56]). In our models, the standard error for the effect of weekly binge drinking in girls was 0.09 in the traditional regression, compared to 0.54 in the IV model.

53. Moreover, IV models only estimate the local average treatment effect (LATE) of the IV (Pokropek, 2016[56]) – meaning it only estimates the impact of alcohol on GPA in those students whose drinking is affected by how much their friends drink. It can be argued that not all students are affected by their peers' drinking habits, and the LATE estimated by the IV models may therefore be different from the average treatment effect (ATE) in the overall population.

54. Nevertheless – while the effect size estimated by the IV models may not be accurate, they do suggest a significant, negative impact of alcohol use on GPA.

55. There was no strongly significant relation between the frequency of drinking or binge drinking and test scores in New Zealand when using an adjusted lagged regression. Instrumental variable models did find some significant effects for girls, but since the IVs were weak these cannot be reliably interpreted.

3.3.2. The relationship between the frequency of alcohol use and educational attainment was different across countries

56. In the United Kingdom, no strongly significant relationship was found between the frequency of alcohol use and completing higher education. However, there was a significant negative association between alcohol use and the age at which individuals left full time education. For girls in the United Kingdom, weekly drinking was significantly associated with leaving full-time education 0.35 (0.09 to 0.62) years earlier compared to girls who never or rarely drank. The instrumented models confirmed these findings: weekly drinking was associated with leaving full-time education 0.96 (0.27 to 1.66) years earlier. However, there was no evidence of endogeneity to indicate that the IV model should be used.

57. There was also a clear negative relationship between binge drinking more than once in two weeks and educational attainment in the United Kingdom. Both boys and girls saw a decrease in the number of years spent in full-time education, by 0.60 (0.21 to 0.99) and 0.56 (0.22 to 0.89) years respectively, compared to those who never binge drank. While for boys this negative relationship was no longer significant when using the instrumented model, for girls the effect remained: binge drinking more than once in the last two weeks was associated with leaving full-time education 1.63 (0.38 to 2.88) years earlier. For girls, there was some evidence of endogeneity, which would favour the IV model. While the effect size increased in the IV model compared to the non-instrumented model, the confidence interval was also larger – a common issue with IV models.

58. In New Zealand, the frequency of alcohol use was not significantly associated with completing any higher education in the lagged regression models. However, weekly drinking was associated with a 0.557 (0.004 to 1.110) year decrease in the age at which boys left full-time education. The instrumented models did not find any significant effects,

but there was also no evidence of endogeneity – indicating that the non-instrumented models could be preferred.

59. In the United States, the frequency of alcohol use did not appear to be associated with educational attainment for boys. For girls on the other hand, there was a clear negative relation. Girls who drank weekly were 21% less likely to complete higher education than those who rarely or never drank (RR: 0.79, 0.65 to 0.96), and girls who binge drank weekly were 32% less likely (RR: 0.68, 0.51 to 0.92).

60. However, there was strong evidence of endogeneity, and IV models were run to correct for this. The IV models confirmed the results of the lagged regression models: weekly drinking, weekly binge drinking and the number of units drunk per week were all negatively associated with the likelihood of completing higher education for girls in the United States.

61. In Russia, a positive relationship was found between monthly drinking and completing higher education: girls who drank monthly were 56% (RR: 1.56, 1.15 to 2.12) more likely to completed higher education. However, no significant relation was found between weekly drinking and educational attainment.

4. Section IV – Discussion

4.1. Policy implications of the results

62. There are a number of pathways through which risk factors such as obesity and alcohol use can influence educational outcomes, as detailed section 4.3. This study aimed to explore this causal relation between alcohol use, obesity, and educational outcomes, specifically educational performance and attainment. By using econometric methods it attempted to account for endogeneity due to unobserved confounding and reverse causation.

63. For policymakers and public health professionals, the results of this study emphasise the need to address obesity and alcohol use in children.

64. This study presents evidence that obesity has a negative impact on educational outcomes. But – while significant – the size of the effect was small in all countries. In some cases the effects identified using a lagged regression were lost when using fixed effects models or instrumental variables - suggesting that part of the relation was caused by reverse causality or unobserved confounding. However, in both the German and the United Kingdom dataset a negative relation remained even in the instrumented models. The fixed effects model that was run on German data suggested a negative relation between obesity and educational performance, but similar analyses on United States and Russian data did not confirm this.

65. There was a clear negative relation between frequent alcohol use or frequent binge drinking and educational performance in the Unites States, for both boys and girls. Weekly binge drinking had the greatest effect, potentially reducing a student's score form the 50th to the 40th percentile. The IV models, which account for the endogeneity in the model, suggest that this may be a causal effect. On the other hand, in New Zealand most associations between alcohol use and educational performance were not significant.

66. Alcohol use was associated with a lower educational attainment for girls in the United States and the United Kingdom, and for boys in New Zealand. For the first two, IV models confirmed the findings, suggesting a potential causal relationship between alcohol use and the likelihood of completing higher education for girls. The only except was Russia, where monthly alcohol use was associated with a higher likelihood of completing higher education for girls compared to rarely, never or weekly drinking. However, no instrumental variables were available, and the causal relation could therefore not be tested beyond a lagged regression model.

67. Overall, the results of this study suggest that the presence of risk factors at a young age can affect educational outcomes. Education is associated with the formation of human capital, future individual social-economic status and national income, and this relation can therefore multiply the impact of obesity and alcohol on society and the economy. Policymakers should therefore invest in programmes and policies to reduce childhood obesity and alcohol consumption.

4.2. Discussion of the methods

68. This study used different methodological approaches to establish causality. Longitudinal datasets were used to run lagged regressions and establish a temporal relation between the exposure and the outcome. Instrumental variables were used to address endogeneity caused by potential reverse causality and unobserved confounders, and fixed effects analyses were used to correct for potential unobserved time-invariant confounders. In some cases, the IV or fixed effect analyses found no significant effect where the lagged models did – indicating that there was some other explanation for the observed effect. However, there were several instances where the IV or fixed effect models did find significant effects, suggesting that the relation may be causal.

69. The results of non-instrumented models were presented alongside the instrumented models because of the limitations associated with IV models. IVs models are less precise and produce larger standard errors (Pokropek, 2016[56]) (Crown, Henk and Vanness, 2011[50]). In addition, the reliability of IV analysis is largely dependent on the quality of the instruments. The difficulty of selecting instrumental variables that are strongly correlated to the exposure, and exogenous (i.e. only correlated to the outcome through the exposure), is widely acknowledged as major drawback of IV analysis (Crown, Henk and Vanness, 2011[50]) (Greenland, 2000[57]) (French and Popovici, 2011[58]).

70. First-stage tests confirmed that in the large majority of models the instruments were strongly correlated with the exposure. However, it is not possible to test whether the instruments are exogenous, and this condition must be satisfied based on theoretical considerations.

71. This study selected IVs based on their availability across the different datasets and their widespread use in other studies. Parental BMI was used as instrument for BMI in children (Black, Johnston and Peeters, 2015[59]) (von Hinke Kessler Scholder et al., 2012[60]) and variables related to peer use of alcohol were used for children’s alcohol use (Austin, 2012[61]) (Devaux and Sassi, 2015[62]). It also explored religion as an IV for alcohol use in the United States and United Kingdom datasets, but this was found to be a weak instrument.

72. Despite their use in the academic literature, there are reasons to believe these IVs are not fully exogenous. Parental BMI and the genetic determinants of this may be linked to genetic determinants of educational performance. Moreover, there may be unobserved confounders at the household or family level that influence both parental and child BMI (Black, Johnston and Peeters, 2015[59]). Using friends of the respondent to measure peer alcohol use can also be endogenous, since friend selection is not random. The possibility that the IVs are not exogenous should be recognised as an important limitation of the results.

73. In many cases fixed effect models could not be run, as there was only one time point available with both the exposure and the outcome. In many cases no significant effect was found. This may have been the result of the short follow-up period. All the fixed effect analyses compared exposure and outcomes over a period of one year, in which changes may have been small. Only in one case (the effect of obesity on educational performance in Russia) were there enough data points to run a lagged fixed effect model – however this analysis also found no significant effects.

74. Due to the fact that each method has its limitations, as described above, this study considers the results of the different methods alongside each other. This approach allows the causal relationship to be tested under different assumptions and constraints.

4.3. Limitations of the data

75. An important limitation of this study – and indeed of many studies relying on longitudinal study data – is missing data and non-response. In the case of the United Kingdom data, the educational performance data was affected by a teachers' strike and could not be used for analysis. The German data sample also had a considerable non-response in each wave, and weightings were used to correct for this.

76. The diverging results that were found across countries may be the result of the national context; but they may also be caused by differences in the data. All cohorts collected data at different ages and at different intervals. While efforts were made to standardise the variables used for analysis, the data collected in each cohort was not always fully comparable. In particular confounding variables on socio-economic status and ethnicity/migrant status varied across datasets, and may have caused differences in the results. Moreover, the known difference between self-reported and measured BMI may have also contributed to differences between the countries (Devaux et al., 2011[27]). As a result, it is not possible to compare countries in terms of effect size.

77. Under-reporting of alcohol use is a widely recognised issue with studies that use self-reported alcohol consumption data. While most participants underestimate their consumption, the degree to which consumption is underreported varies by gender, age and drinking pattern (Boniface, Kneale and Shelton, 2014[63]) (Livingston and Callinan, 2015[64]). This may have affected the results in this study, in particular the results based on the Russian data set. The estimates of alcohol consumption in the RLMS database have been reported to be unreliable (Nemtsov, 2004[65]).

78. The inclusion of smoking as a confounder had a considerable impact on the results of the analyses on alcohol. A number of highly significant effects became non-significant, and in other cases effects became significant. Other studies have also included smoking status as a confounder (Chatterji, 2006[46]) (Sabia, 2010[44]) (Meda et al., 2017[43]) (Silins et al., 2015[45]) (Balsa, Giuliano and French, 2011[18]). Smoking and alcohol use are known to be closely related risk behaviours, and further research is needed to fully understand the interplay between alcohol use, smoking, and educational outcomes.

4.4. Conclusion

79. The results of this study suggest that the presence of risk factors – obesity and alcohol use – at a young age can, in some cases, affect educational outcomes. As education is associated with the formation of human capital, future individual social-economic status and national income, this effect can multiply the impact of obesity and alcohol on society and the economy.

80. This study compared different econometric methods to identify whether a causal relationship exists: lagged regression, instrumental variable models and fixed effect models. These methods all present with limitations that are important to understand when interpreting the results. However, taken together they provide some evidence to suggest that there may be a causal relationship between obesity, alcohol use and educational outcomes.

81. Nevertheless, it remains difficult to confidently identify and quantify the causal relation between risk factors and educational outcomes. More research is needed to understand the complex interactions between alcohol use, obesity, educational outcomes and other social and economic factors – in particular smoking.

Box 4.1. What does this study tell us?

- There is evidence to suggest that obesity and alcohol use have a negative, causal impact on educational performance and attainment.
- Evidence was found in several countries of the relationship between obesity and educational outcomes: students who were obese during their high school years had lower grades, were 20% less likely to attend a higher level of high school, and were 28% to 58% less likely to complete higher education
- Similarly, a relationship between alcohol use and educational outcomes was identified in some countries: frequent binge drinking was associated with a 10-percentile drop in GPA from the median, and students who drank weekly left full-time education 0.35 to 0.56 years earlier and were 21% less likely to complete higher education.
- A number of approaches can be used to test for a causal relationship between obesity, alcohol use and educational outcomes. Overall, different methods often produced similar results in terms of identifying significant relationships, particularly lagged regression and instrumental variable models. Fixed effect analyses were more likely not to identify a significant relationship, but this may have been due to the short follow-up times available for these analyses.

5. Annex I: Detailed results

5.1. Obesity and educational performance

Table 5.1. Results of obesity and educational performance analyses

Country	Outcome	Method	Exposure	Male	Female
United States	GPA (1 to 4)	Lagged linear regression	Obesity (vs normal weight)	Coefficient: -0.11*	**Coefficient: -0.26*** **
			Overweight (vs normal weight)	Coefficient: -0.00	**Coefficient: -0.15*** **
			BMI	**Coefficient: -0.01** **	**Coefficient: -0.02*** **
			BMI (quadratic)	**Coefficient: -0.0002** **	**Coefficient: -0.0004*** **
		Linear regression with fixed effects	BMI	Coefficient: -0.0099	Coefficient: -0.0003
			BMI (quadratic)	Coefficient: -0.00017	Coefficient: -0.00001
Russia	Average grade (1 to 5)	Lagged linear regression	Obesity (vs normal weight)	Coefficient: 0.03	**Coefficient: -0.11*** **
			Overweight (vs normal weight)	Coefficient: 0.03	Coefficient: -0.02
			BMI	**Coefficient: 0.01** **	**Coefficient: -0.01*** **
			BMI (quadratic)	Coefficient: 0.0001*	**Coefficient: -0.0001** **
		Linear regression with fixed effects	BMI	Coefficient: -0.0008	Coefficient: -0.0008
			BMI (quadratic)	Coefficient: -0.0000085	Coefficient: 0.0000003
		Lagged linear regression with fixed effects	BMI	Coefficient: -0.0028	Coefficient: -0.0031
			BMI (quadratic)	Coefficient: -0.00005	Coefficient: -0.00003
Germany	Average grade *(6 to 1; NOTE: lower grade is better performance)*	Lagged linear regression	Obesity (vs normal weight)	Coefficient: 0.08	Coefficient: 0.05
			Overweight (vs normal weight)	Coefficient: 0.06	Coefficient: -0.02
			BMI	Coefficient: 0.01	Coefficient: -0.01
			BMI (quadratic)	Coefficient: 0.0162	Coefficient: -0.0002
		Linear regression with fixed effects	BMI	**Coefficient: 0.04** **	Coefficient: 0.03*
			BMI (quadratic)	**Coefficient: 0.0009** **	Coefficient: 0.0004
		Lagged linear regression with IV	BMI	**Coefficient: 0.08** (Strong IVs, strong evidence of endogeneity)**	Coefficient: 0.04* (Strong IVs, strong evidence of endogeneity)
			BMI (quadratic)	**Coefficient: 0.002** (Strong IVs, strong evidence of endogeneity)**	Coefficient: 0.001* (Strong IVs, strong evidence of endogeneity)

Country	Outcome	Method	Exposure	Male	Female
Netherlands	% higher level of high school	Lagged logistic regression	Overweight and obese (vs normal weight)	**Risk ratio: 0.80*** **	Risk ratio: 0.89
			BMI	**Odds ratio: 0.91*** **	Odds ratio: 0.94*
			BMI (quadratic)	**Odds ratio: 0.997*** **	Odds ratio: 0.998*
		Lagged probit regression with IV	Overweight and obese (vs normal weight)	Coefficient: -0.46 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.79 (Strong IVs, but no evidence of endogeneity)
			BMI	Coefficient: -0.07 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.10 (Strong IVs, but no evidence of endogeneity)
	% below teacher assessment level high school	Lagged logistic regression	Overweight and obese (vs normal weight)	Risk ratio: 0.79	Risk ratio: 0.82
			BMI	Odds ratio: 0.98	Odds ratio: 1.003
			BMI (quadratic)	Odds ratio: 0.999	Odds ratio: 1.00002
		Lagged probit regression with IV	Overweight and obese (vs normal weight)	Coefficient: -0.25 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.78 (Strong IVs, but no evidence of endogeneity)
			BMI	Coefficient: -0.04 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.08 (Strong IVs, but no evidence of endogeneity)

Note: *: significant at 0.1 level; ****: significant at 0.05 level; ***: significant at 0.01 level**
Results shown are adjusted for age, ethnicity or minority status, social class and/or income, and alcohol consumption (United States only). IVs for Germany and the Netherlands were BMI of mother and BMI of father. The coefficients of linear regression models can be interpreted as the increase in outcome for each unit increase in exposure; the coefficients of probit models cannot be directly interpreted in terms of effect size, but do show the direction of the effect (positive or negative depending on whether the coefficient is positive or negative); relative risks show how much more or less likely one group is to experience the outcome, with a value greater than one signifying a higher likelihood; odds ratios are similar to risk ratios but are based on odds rather than risk. For details on the tests run on the IV analyses please refer to Annex IV.

5.2. Obesity and educational attainment

Table 5.2. Results of obesity and educational attainment analyses

Country	Outcome	Method	Exposure	Male	Female
United States	Any higher education	Lagged log-binomial regression	Obesity (vs normal weight)	Risk ratio: 0.88	**Risk ratio: 0.72*** **
			Overweight (vs normal weight)	Risk ratio: 0.97	**Risk ratio: 0.79*** **
			BMI	Risk ratio: 1.00	**Risk ratio: 0.98*** **
			BMI (quadratic)	Risk ratio: 0.9999	**Risk ratio: 0.9995*** **
United Kingdom	Any higher education	Lagged log-binomial regression (or logistic regression for odds ratio)	Obesity (vs normal weight)	**Risk ratio: 0.42** **	Risk ratio: 1.02
			Overweight (vs normal weight)	Risk ratio: 0.83	Risk ratio: 0.86
			Overweight and obese (vs normal weight)	**Risk ratio: 0.76** **	Risk ratio: 0.88
			BMI	**Odds ratio: 0.95** **	Risk ratio: 0.98*
			BMI (quadratic)	**Odds ratio: 0.9987** **	**Risk ratio: 0.9996** **
		Lagged probit regression with IV	BMI	**Coefficient: -0.103** (Weak IVs)**	**Coefficient: -0.130*** (Strong IVs, strong evidence of endogeneity)**
			BMI (quadratic)	**Coefficient: -0.002** (Weak IVs)**	**Coefficient: -0.003*** (Strong IVs, strong evidence of endogeneity)**
	Age left FT education	Lagged linear regression	Obesity (vs normal weight)	Coefficient: -0.91*	Coefficient: -0.35
			Overweight (vs normal weight)	Coefficient: -0.19	Coefficient: -0.35*
			Overweight and obese (vs normal weight)	Coefficient: -0.33	Coefficient: -0.35*
			BMI	Coefficient: -0.04*	**Coefficient: -0.04** **
			BMI (quadratic)	Coefficient: -0.0008*	**Coefficient: -0.0010** **
		Lagged linear regression with IV	BMI	**Coefficient: -0.20** (Strong IVs, some evidence of endogeneity)**	**Coefficient: -0.23*** (Strong IVs, strong evidence of endogeneity)**
			BMI (quadratic)	Coefficient: -0.004* (Strong IVs, some evidence of endogeneity)	**Coefficient: -0.005*** (Strong IVs, strong evidence of endogeneity)**
Russia	Any higher education	Lagged log-binomial regression	Overweight and obese (vs normal weight)	Risk ratio: 0.73	Risk ratio: 0.94
			BMI	Risk ratio: 1.04	Risk ratio: 0.98
			BMI (quadratic)	Risk ratio: 1.0009	Risk ratio: 0.9995

Note: *: significant at 0.1 level; ****: significant at 0.05 level; ***: significant at 0.01 level**
Results shown are adjusted for age, ethnicity or minority status, social class and/or income, smoking status (except for the United States), and alcohol consumption. IVs for the United Kingdom were BMI of mother and BMI of father. The coefficients of linear regression models can be interpreted as the increase in outcome for each unit increase in exposure; the coefficients of probit models cannot be directly interpreted in terms of effect size, but do show the direction of the effect (positive or negative depending on whether the coefficient is positive or negative); relative risks show how much more or less likely one group is to experience the outcome, with a value greater than one signifying a higher likelihood; odds ratios are similar to risk ratios but are based on odds rather than risk. For details on the tests run on the IV analyses please refer to Annex IV.

5.3. Alcohol and educational performance

Table 5.3. Results of alcohol use and educational performance analyses

Country	Outcome	Method	Exposure	Male	Female
United States	GPA (1 to 4)	Lagged linear regression	Monthly drinking (vs rarely or never drinking)	**Coefficient: -0.11****	**Coefficient: -0.11****
			Weekly drinking (vs rarely or never drinking)	**Coefficient: -0.19*****	**Coefficient: -0.20*****
			Units per month	Coefficient: -0.0008	**Coefficient: -0.0026*****
			Monthly binging (vs rarely or never binging)	**Coefficient: -0.21*****	**Coefficient: -0.22*****
			Weekly binging (vs rarely or never binging)	**Coefficient: -0.25*****	**Coefficient: -0.21****
		Linear regression with fixed effects	Units per month	Coefficient: 0.0001	Coefficient: 0.0001
		Lagged linear regression with IV	Weekly drinking (vs monthly or rarely or never)	**Coefficient: -1.12*** (Strong IVs, strong evidence of endogeneity)**	**Coefficient: -1.67*** (Strong IVs, strong evidence of endogeneity)**
			Units per month	**Coefficient: -0.011*** (Strong IVs, strong evidence of endogeneity)**	**Coefficient: -0.017*** (Strong IVs, strong evidence of endogeneity)**
			Weekly binging (vs monthly or rarely or never)	**Coefficient: -1.57*** (Strong IVs, strong evidence of endogeneity)**	**Coefficient: -2.36*** (Strong IVs, strong evidence of endogeneity)**
		Linear regression with fixed effects and IV	Units per month	Coefficient: -0.001 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.012* (Moderately strong IVs, strong evidence of endogeneity)
New Zealand	BURT reading score (up to 110)	Lagged linear regression	Monthly drinking (vs rarely or never drinking)	Coefficient: -1.16	Coefficient: 1.60
			Weekly drinking (vs rarely or never drinking)	Coefficient: -1.66	Coefficient: -0.90
			Monthly binge drinking (vs rarely or never binge drinking)	Coefficient: 0.47	Coefficient: 2.43
			Weekly binge drinking (vs rarely or never binge drinking)	Coefficient: -2.38	Coefficient: 0.99
		Lagged linear regression with IV	Weekly drinking (vs monthly or rarely or never)	Coefficient: 4.12 (Strong IVs, but no evidence of endogeneity)	Coefficient: 18.00* (Weak IVs)
			Weekly binge drinking (vs monthly or rarely or never)	Coefficient: 4.73 (Strong IVs, but no evidence of endogeneity)	**Coefficient: 25.50** (Weak IVs)**

Note: *: significant at 0.1 level; ****: significant at 0.05 level; ***: significant at 0.01 level;**
Results shown are adjusted for age, ethnicity or minority status, social class and/or income, and BMI (except for New Zealand where this information was not available). IVs for New Zealand are "how many friends use alcohol – none, some or most" at age 15 and 16, and for the United States "how many of your best friends drink". The coefficients of linear regression models can be interpreted as the increase in outcome for each unit increase in exposure. For details on the tests run on the IV analyses please refer to Annex IV.

5.4. Alcohol and educational attainment

Table 5.4. Results of alcohol use and educational attainment analyses

Country	Outcome	Method	Exposure	Male	Female
US	Any higher education	Lagged log-binomial regression	Monthly drinking (vs rarely or never drinking)	Risk ratio: 0.95	Risk ratio: 0.95
			Weekly drinking (vs rarely or never drinking)	Risk ratio: 0.94	**Risk ratio: 0.79****
			Units per month	Risk ratio: 0.999	**Risk ratio: 0.996****
			Monthly binging (vs rarely or never binging)	Risk ratio: 1.0026	Risk ratio: 1.0002
			Weekly binging (vs rarely or never binging)	Risk ratio: 0.80*	**Risk ratio: 0.68****
		Lagged probit regression with IV	Weekly drinking (vs monthly or rarely or never)	Coefficient: -0.34 (Strong IVs, but no evidence of endogeneity)	**Coefficient: -1.79*** (Strong IVs, strong evidence of endogeneity)**
			Units per month	Coefficient: -0.003 (Strong IVs, but no evidence of endogeneity)	**Coefficient: -0.016*** (Strong IVs, strong evidence of endogeneity)**
			Weekly binging (vs monthly or rarely or never)	Coefficient: -0.47 (Strong IVs, but no evidence of endogeneity)	**Coefficient: -2.70*** (Strong IVs, strong evidence of endogeneity)**
Russia	Any higher education	Lagged log-binomial regression	Monthly drinking (vs rarely or never drinking)	Risk ratio: 1.54*	**Risk ratio: 1.56*****
			Weekly drinking (vs rarely or never drinking)	Risk ratio: 1.25	Risk ratio: 1.42
UK	Any higher education	Lagged log-binomial regression (or logistic regression for odds ratio)	Monthly drinking (vs rarely or never drinking)	Risk ratio: 1.20*	Risk ratio: 1.03
			Weekly drinking (vs rarely or never drinking)	Risk ratio: 1.10	Risk ratio: 0.93
			Units per week	Odds ratio: 0.98*	Risk ratio: 0.99
			Binging once in last 2 weeks (vs not binging)	Risk ratio: 1.13	Risk ratio: 1.01
			Binging more than once last 2 weeks (vs not binging)	Risk ratio: 0.83*	Risk ratio: 0.86*
		Lagged probit regression with IV	Weekly drinking (vs monthly or rarely or never)	Coefficient: 0.04 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.06 (Strong IVs, but no evidence of endogeneity)
			Units per week	Coefficient: 0.002 (Strong IVs, but no evidence of endogeneity)	Coefficient: 0.005 (Strong IVs, but no evidence of endogeneity)
			Binging more than once last 2 weeks (vs less often)	Coefficient: 0.05 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.07 (Strong IVs, but no evidence of endogeneity)

Country	Outcome	Method	Exposure	Male	Female
	Age left FT education	Lagged linear regression	Monthly drinking (vs rarely or never drinking)	Coefficient: 0.46*	Coefficient: 0.3
			Weekly drinking (vs rarely or never drinking)	Coefficient: 0.04	**Coefficient: -0.35*** **
			Units per week	Coefficient: -0.02	**Coefficient: -0.03** **
			Binging once in last 2 weeks (vs not binging)	Coefficient: -0.02	Coefficient: 0.10
			Binging more than once last 2 weeks (vs not binging)	**Coefficient: -0.60*** **	**Coefficient: -0.56*** **
		Lagged linear regression with IV	Weekly drinking (vs monthly or rarely or never)	Coefficient: -0.21 (Strong IVs, but no evidence of endogeneity)	**Coefficient: -0.96*** (Strong IVs, but no evidence of endogeneity)**
			Units per week	Coefficient: -0.01 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.04 (Strong IVs, but no evidence of endogeneity)
			Binging more than once last 2 weeks (vs less often)	Coefficient: -0.35 (Strong IVs, but no evidence of endogeneity)	**Coefficient: -1.63** (Strong IVs, some evidence of endogeneity)**
NZ	Any higher education	Lagged logistic regression	Monthly drinking (vs rarely or never drinking)	Risk ratio: 0.99	Risk ratio: 0.87
			Weekly drinking (vs rarely or never drinking)	Risk ratio: 1.04	Risk ratio: 0.91
			Monthly binge drinking (vs rarely or never binge drinking)	Risk ratio: 0.98	Risk ratio: 0.72*
			Weekly binge drinking (vs rarely or never binge drinking)	Risk ratio: 0.97	Risk ratio: 1.17
		Lagged probit regression with IV	Weekly drinking (vs monthly or rarely or never)	Coefficient: 0.94* (Strong IVs, some evidence of endogeneity)	Coefficient: 0.13 (Weak IVs)
			Weekly binge drinking (vs monthly or rarely or never)	Coefficient: 1.18 (Strong IVs, strong evidence of endogeneity)	Coefficient: 0.63 (Weak IVs)
	Age left FT education	Lagged linear regression	Monthly drinking (vs rarely or never drinking)	Coefficient: -0.28	Coefficient: 0.27
			Weekly drinking (vs rarely or never drinking)	**Coefficient: -0.56** **	Coefficient: 0.17
			Monthly binge drinking (vs rarely or never binge drinking)	Coefficient: -0.48	Coefficient: 0.52*
			Weekly binge drinking (vs rarely or never binge drinking)	Coefficient: -0.62*	Coefficient: 0.38

Country	Outcome	Method	Exposure	Male	Female
		Lagged linear regression with IV	Weekly drinking (vs monthly or rarely or never)	Coefficient: -0.57 (Strong IVs, but no evidence of endogeneity)	Coefficient: 0.26 (Weak IVs)
			Weekly binge drinking (vs monthly or rarely or never)	Coefficient: -1.06 (Strong IVs, but no evidence of endogeneity)	Coefficient: -0.11 (Weak IVs)

Note: *: significant at 0.1 level; **: significant at 0.05 level; ***: significant at 0.01 level**
Results shown are adjusted for age, ethnicity or minority status, social class and/or income, smoking status (except for the United States), and BMI (except for New Zealand where this information was not available). IVs for New Zealand are "how many friends use alcohol – none, some or most" at age 15 and 16; for the United Kingdom "who drinks out of older sister, brother, boyfriend or girlfriend, best friend, next best friend" measured as both a count and a percentage; for the United States "how many of your best friends drink". The coefficients of linear regression models can be interpreted as the increase in outcome for each unit increase in exposure; the coefficients of probit models cannot be directly interpreted in terms of effect size, but do show the direction of the effect (positive or negative depending on whether the coefficient is positive or negative); relative risks show how much more or less likely one group is to experience the outcome, with a value greater than one signifying a higher likelihood; odds ratios are similar to risk ratios but are based on odds rather than risk. For details on the tests run on the IV analyses please refer to Annex IV.

6. Annex II: Descriptive statistics by risk factor group

Table 6.1. Educational performance

		Not obese	Obese	Rarely drinking	Monthly drinking	Weekly drinking
United States: Grade point average, 1 to 4	Male	2.71	2.59	2.72	2.65	2.54
	Female	2.98	2.70	2.97	2.87	2.77
Russia: Average grade, 1 to 5	Male	4.03	4.06			
	Female	4.30	4.19			
Germany: Average grade, 6 to 1*	Male	2.65	2.89			
	Female	2.47	2.66			
Netherlands:** % of students at higher level of high school	Male	68%	51%			
	Female	71%	54%			
New Zealand: BURT reading score, up to 110	Male			97.23	96.18	94.12
	Female			98.16	99.51	94.67

Note: All exposures are lagged to the educational outcomes, e.g. obesity was measured in wave t-1 and compared to grades in wave t=0.
* Grades in Germany are measured on an inverted scale, where a higher number equals a lower performance
** For the Netherlands, obesity and overweight were combined due to the low prevalence of obesity

Table 6.2. Educational attainment

% of students completing higher education		Not obese	Obese	Rarely drinking	Monthly drinking	Weekly drinking
United Kingdom	Male	34%	19%	33%	41%	37%
	Female	32%	22%	35%	36%	33%
United States	Male	34%	29%	33%	34%	31%
	Female	44%	31%	44%	41%	33%
Russia**	Male	32%	27%	30%	28%	21%
	Female	37%	26%	34%	45%	40%
New Zealand	Male			36%	37%	33%
	Female			55%	48%	37%

Note: All exposures are lagged to the educational outcomes, e.g. obesity was measured during school years and compared to educational attainment at the age of 29 or 35.
** For Russia, obesity and overweight were combined due to the low prevalence of obesity

7. Annex III: Results of instrumental variable tests

Table 7.1. Results of the instrumental variable tests for the obesity analyses

Country	Outcome	Method	Exposure	Male			Female		
				F statistic	*Reference value*	Test of endogeneity	F statistic	*Reference value*	Test of endogeneity
Germany	Average grade	Lagged linear regression with IV	BMI	**97.46**	*19.93*	**0.022**	**170.91**	*19.93*	**0.020**
			BMI (quadratic)	**953.35**	*19.93*	**0.022**	**166.83**	*19.93*	**0.032**
Netherlands	Higher level of high school	Lagged probit regression with IV	Overweight and obese (vs normal weight)	**17.76**	*10*	0.689	**12.49**	*10*	0.219
			BMI	**20.89**	*10*	0.705	**15.31**	*10*	0.289
	Below advice level high school	Lagged probit regression with IV	Overweight and obese (vs normal weight)	**13.86**	*10*	0.780	**12.81**	*10*	0.327
			BMI	**17.37**	*10*	0.770	**15.43**	*10*	0.398
UK	Any higher education	Lagged probit regression with IV	BMI	9.04	*10*	0.114	**16.03**	*10*	**0.001**
			BMI (quadratic)	6.20	*10*	0.143	**14.36**	*10*	**0.001**
	Age left FT education	Lagged linear regression with IV	BMI	**45.70**	*19.93*	0.098	**90.82**	*19.93*	**0.007**
			BMI (quadratic)	**30.69**	*19.93*	0.097	**81.43**	*19.93*	**0.008**

Note: **Bold**: F statistic is larger than the reference value (which is based on the Stock-Yogo critical value for maximum 10% bias (Stock and Yogo, 2005[66]) for continuous outcomes, or set at 10 (Staiger and Stock, 1997[67]) for binary outcomes where the Stock-Yogo values are not available), indicating that the instruments are strong; or p-value for the test of endogeneity is less than 0.05 and the null hypothesis of no endogeneity can be rejected.

Table 7.2. Results of the instrumental variable tests for the alcohol analyses

Country	Outcome	Method	Exposure	Male			Female		
				F statistic	*Reference value*	Test of endogeneity	F statistic	*Reference value*	Test of endogeneity
US	GPA	Lagged linear regression with IV	Weekly drinking (vs monthly or rarely)	**211.21**	*16.38*	**0.000**	**144.17**	*16.38*	**0.000**
			Units per month	**143.51**	*16.38*	**0.000**	**149.07**	*16.38*	**0.000**
			Weekly binging (vs monthly or rarely)	**132.86**	*16.38*	**0.000**	**110.07**	*16.38*	**0.000**
		Linear regression with fixed effects and IV	Units per month	**44.52**	*16.38*	0.548	15.26	*16.38*	0.034
	Any higher education	Lagged probit regression with IV	Weekly drinking (vs monthly or rarely)	**43.68**	*10*	0.272	**21.79**	*10*	**0.000**
			Units per month	**26.77**	*10*	0.428	**23.81**	*10*	**0.002**
			Weekly binging (vs monthly or rarely)	**27.87**	*10*	0.512	**13.41**	*10*	**0.000**
NZ	BURT reading score	Lagged linear regression with IV	Weekly drinking (vs monthly or rarely)	**31.72**	*19.93*	0.326	10.89	*19.93*	0.013
			Weekly binge drinking (vs monthly or rarely)	**23.95**	*19.93*	0.336	9.19	*19.93*	0.023
	Any higher education	Lagged probit regression with IV	Weekly drinking (vs monthly or rarely)	**10.66**	*10*	0.053	7.03	*10*	0.867
			Weekly binge drinking (vs monthly or rarely)	**11.97**	*10*	**0.049**	5.84	*10*	0.795
	Age left FT education	Lagged linear regression with IV	Weekly drinking (vs monthly or rarely)	**31.37**	*19.93*	0.822	10.57	*19.93*	0.866
			Weekly binge drinking (vs monthly or rarely)	**23.72**	*19.93*	0.543	8.98	*19.93*	0.879

Country	Outcome	Method	Exposure	Male			Female		
UK	Any higher education	Lagged probit regression with IV	Weekly drinking (vs monthly or rarely)	**26.79**	*10*	0.961	**38.50**	*10*	0.855
			Units per week	**26.04**	*10*	0.384	**38.52**	*10*	0.522
			Binging more than once last 2 weeks (vs less often)	**22.13**	*10*	0.331	**25.73**	*10*	0.791
	Age left FT education	Lagged linear regression with IV	Weekly drinking (vs monthly or rarely)	**116.21**	*19.93*	0.807	**163.77**	*19.93*	0.120
			Units per week	**88.32**	*19.93*	0.731	**72.77**	*19.93*	0.930
			Binging more than once last 2 weeks (vs less often)	**96.39**	*19.93*	0.618	**87.17**	*19.93*	0.086

Note: **Bold**: F statistic is larger than the reference value (which is based on the Stock-Yogo critical value for maximum 10% bias (Stock and Yogo, 2005[66]) for continuous outcomes, or set at 10 (Staiger and Stock, 1997[67]) for binary outcomes where the Stock-Yogo values are not available), indicating that the instruments are strong; or p-value for the test of endogeneity is less than 0.05 and the null hypothesis of no endogeneity can be rejected.

8. Annex IV: Econometric methods to establish causality

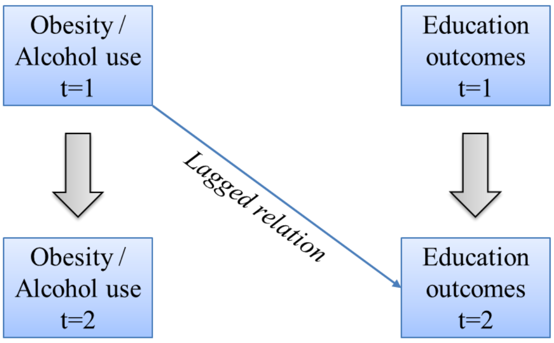
8.1. Lagged regression

To establish causality, three criteria need to be met (Oppewal, 2010[48]) (Antonakis et al., 2014[68]):

- Covariation
- Absence of alternative explanations
- Temporal precedence

Covariation between the risk factors and obesity can easily be shown through regression analyses. By including confounders – factors which influence both the exposure and the outcome – in the regression model, it is possible to control for known alternative explanations. To establish whether there is a temporal relation between the exposure (obesity or alcohol use) and the outcomes (educational performance or attainment), longitudinal data can be used for the regression analysis. This allows the exposure to be measured in one wave, and the outcome in a later wave – to ensure the exposure preceded the outcome (see Figure 8.1).

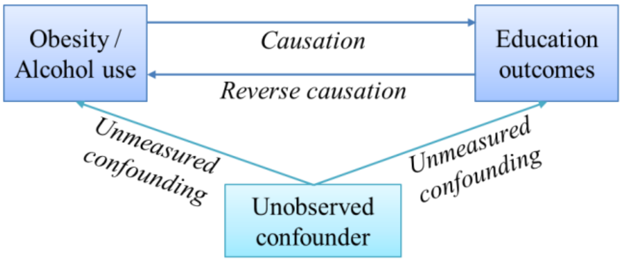
Figure 8.1. Lagged analysis to establish temporal precedence



In this study, a linear regression was used with a lagged exposure variable (e.g. obesity in the previous wave) for continuous outcome variables (e.g. grades). For binary outcome variables (e.g. completing higher education) a generalised linear model (GLM) model with a binominal family and a log link was used to obtain risk ratios rather than odds ratios. Where no convergence was achieved, the 'difficult' option was added and other algorithms were tried. If the model still failed to achieve convergence, the ODDSRISK function in Stata was used on a wide dataset (as this could not be used on panel data). However ODDSRISK was designed only for binary exposures and outcomes (2x2), and for continuous predictors that failed to converge, odds ratios had to be reported.

One limitation of this approach is that it is only possible to correct for known confounders. However, there may also exist unobserved or omitted confounders that influence the relation (see Figure 8.2). In addition, an alternative explanation for the relation between exposure and outcome can be reverse causality.

Figure 8.2. Schematic overview of causality and alternative explanations



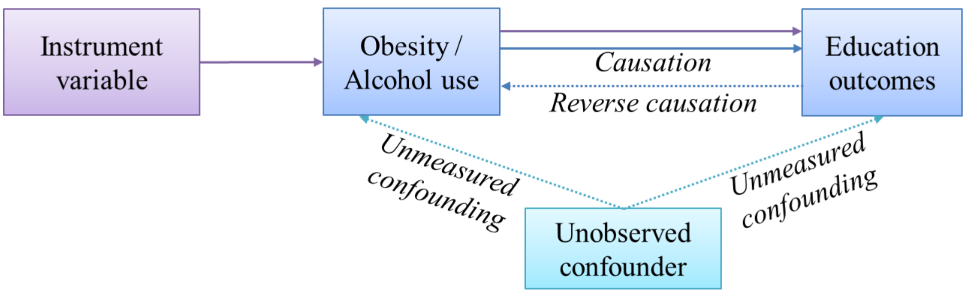
In the case of obesity, alcohol and education, evidence of reverse causality exists, as educated individuals have been shown to have a better understanding of health issues and are less likely to live unhealthy lifestyles (Sassi et al., 2009[15]) (Huerta and Borgonovi, 2010[69]) (Cutler and Lleras-Muney, 2010[70]). In addition, the complex and multifaceted socio-economic nature of these issues makes it likely that there exist unobserved or omitted factors that influence both – related to concepts such as parental education, family income or personal motivation.

In both cases the presence of the alternative explanation introduced endogeneity into the model. Endogeneity arises when one of the predictor (independent) variables is correlated with the error term (Antonakis et al., 2014[68]). To correct for endogeneity, different analysis techniques can be used: instrumental variables can be used to address unobserved confounders and reverse causality; and fixed effects analyses can be used to correct of unobserved time-invariant confounders.

8.2. Instrumental variables

One approach to addressing the issue of endogeneity is to use instrumental variables (Angrist and Pischke, 2008[71]). Instrumental variables (IV) are independent variables that are strongly correlated with the exposure (e.g. obesity), but have no correlation with the outcome (e.g. grades) or any unobserved confounders – other than through their correlation with the exposure (see Figure 8.3). Therefore, the observed correlation between the IV and the outcome is a direct function of the correlation of the exposure and the outcome. IV methods measure the effect of the exposure on the outcome by looking at the relation between the instrument and the outcome, while correcting for the correlation between the IV and the exposure.

Figure 8.3. Schematic overview of instrumental variables



For the binary IV analyses a probit model was applied using the IVPROBIT function in Stata, and for the linear IV analyses the IVREG2 function.

When using IVs, it is important to identify whether there is evidence of endogeneity in the original, non-instrumented model. IVs models are less precise and produce larger standard errors (Pokropek, 2016[56]) (Crown, Henk and Vanness, 2011[50]), so if there is no evidence of endogeneity, traditional regression models may be preferred. For IVPROBIT models, the Wald test of exogeneity was used to test for endogeneity of the non-instrumented model (Wooldridge, 2002[72]). For the IVREG2 models, the presence of endogeneity in the non-instrumented model was tested used the *endog* option.

Moreover, the reliability of the IVs needs to be tested. IVs need to satisfy two conditions (French and Popovici, 2011[58]):

- They need to be "strong", i.e. they need to be significantly correlated with the endogenous exposure variable.
- They need to be exogenous, i.e. they need to be not correlated to the outcome (other than through the exposure), or to any unobserved confounders.

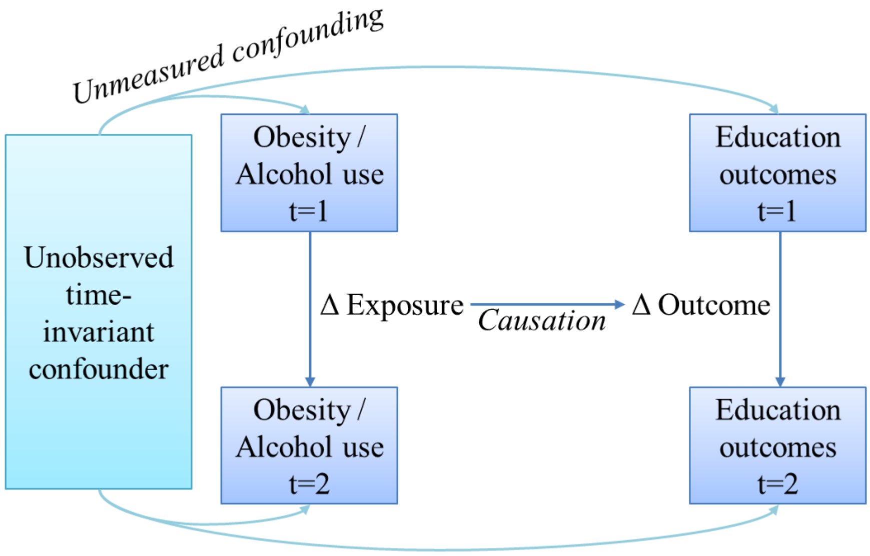
The first condition can be tested by looking at the F statistic of the first stage. The first stage identifies the correlation between the instrument and the endogenous exposure. For IVPROBIT models the F statistic of the first stage model was obtained using the *twostep first* option. The commonly used value of 10 was used as the cut off for strong instruments (Staiger and Stock, 1997[67]). For the IVREG models, the strength of the instruments was evaluated using the Cragg-Donald Wald statistic (Cragg and Donald, 1993[73]), and compared to the Stock-Yogo critical value for a maximum relative bias of 10% (Stock and Yogo, 2005[66]). This threshold was chosen as it was the lowest reported relative bias.

The second condition, however, cannot be tested (French and Popovici, 2011[58]). Instead, the selection of exogenous variables relies on theoretical considerations. In this study, parents' BMI was used as IVs for BMI in the children – a common approach in the literature (Black, Johnston and Peeters, 2015[59]) (von Hinke Kessler Scholder et al., 2012[60]). Variables related to peer use of alcohol were used for children's alcohol use (Austin, 2012[61]) (Devaux and Sassi, 2015[62]). The exact measure of peer alcohol use was dependent on the variables available in the dataset, for example the number of friends that use alcohol or the proportion of siblings and friends that use alcohol (for details see Table 2.2). While it is possible to argue that these IVs are not exogenous, they were selected because of their availability across the datasets and their widespread use in other studies.

8.3. Fixed effects models

A common econometric method that utilises the time dimension of longitudinal data to correct for unobserved time-invariant confounders is the fixed effects model (Angrist and Pischke, 2008[71]). This approach looks at changes in predictors and outcomes within an individual over time (see Figure 8.4). As a result, each individual functions as its own control, providing a perfect correction for any characteristics that do not change over time (such as gender, underlying intelligence, genetics).

Figure 8.4. Schematic overview of a fixed effects model



Fixed effects can be estimated by creating a dummy variable for each individual, which would capture all the unobserved, time-invariant confounders for this individual. A less computationally-intensive method relies on subtracting the mean value of each variable over time from the current observation (Balsa, Giuliano and French, 2011[18]) (Gunasekara et al., 2014[47]) (Angrist and Pischke, 2008[71]). This automatically sets time-invariant variables to zero. (Note that when only two time points are used, the fixed effects model gives the same results as the first-difference approach, which subtracts the values of the previous time points, rather than subtracting the mean over time).

Fixed effects models measure changes in exposure and outcomes within an individual. This approach is therefore less useful when only few respondents change their exposure levels (Gunasekara et al., 2014[1]). Since BMI and units of alcohol exhibit more variation over time than obesity or a binary drinking variable, these exposures were used for the fixed effects models. Moreover, linear fixed effects models are more robust than fixed effects models for count and categorical (including binary) outcomes (Gunasekara et al., 2014[1]). To correct for the expected increase in BMI over time, age was included as a time-variant confounder.

Where more than two time points are available, the fixed effects model can be run with a lagged exposure. For example, the change in obesity between t=1 and t=2 is compared with a change in educational performance between t=2 and t=3. This approach explores whether there is a delayed impact of the exposure on the outcome. However, in most cases only two waves were available that measured both exposure and outcome, making it impossible to run lagged fixed effects models.

9. Annex V: Details of the longitudinal cohorts

9.1. The Add Health cohort

The analysis for the United States is based on data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), 1994-2008. This longitudinal study started with a nationally representative sample of U.S. adolescents in grades 7 through 12 during the 1994-1995 school year. This cohort was followed into young adulthood through four in-home interviews, the most recent one conducted in 2008 when the sample was aged 25-34.

Table 9.1. Metadata per wave for Add Health Public Use data files

	Ages	Year	N
Wave 1	12-21	1994-95	6,504
Wave 2	13-22	1996	4,834
Wave 3	18-28	2001-02	3,947
Wave 4	25-34	2008	5,114

Source: http://www.cpc.unc.edu/projects/addhealth/

For the educational performance analysis, Wave 1 and Wave 2 were used, which were conducted one year apart in 1994-95 and 1996 respectively. Wave 3 was not conducted until 2001-02, by which time even the youngest students in the cohort were 18 and thus mostly out of school. For the educational attainment analysis Wave 4 was used, with Waves 1 as predictors. For Waves 1 and 2, educational performance was measured as grades for four subjects. In Waves 3 and 4, educational attainment was explored. In all Waves, questions were asked about weight, height and alcohol use.

Table 9.2. Overview of variables per wave

	Obesity	Alcohol	Educational outcomes	Educational attainment
Wave 1	Weight & height	Days drinking during past 12 months Number of drinks per day drinking Days drinking more than 5 drinks during past 12 months	Absence from school Held back or skipped a grade Grade for English, mathematics, history, science	N/A
Wave 2	Weight & height	Days drinking during past 12 months Number of drinks per day drinking Days drinking more than 5 drinks during past 12 months	Grade for English, mathematics, history, science	N/A
Wave 3	Weight & height	Days drinking during past 12 months Number of drinks per day drinking Days drinking more than 5 drinks during past 12 months	N/A	What is the highest grade or year of regular school you have completed? Degrees obtained
Wave 4	Weight & height	Days drinking during past 12 months Number of drinks per day drinking Days drinking more than 5 drinks during past 12 months	N/A	What is the highest level of education that you have achieved to date? Degrees obtained

9.1.1. Missing data

All later Waves use Wave 1 as their base population. As a result, the loss-to-follow-up between waves is not monotone: students who missed Wave 2 can have data for Wave 3. Different base samples were therefore used for the educational performance and attainment analyses. For educational performance, the sample consists of 4,834 students from Wave 1 who also participated in Wave 2. For educational attainment, the 5,114 students who participated in Waves 1 and 4 were selected.

The loss-to-follow-up between Wave1 and Wave 2 and 4 was 26% and 21%, respectively. Respondents who were older during Wave 1 were less likely to respond to Wave 2, which may be due to them leaving school and moving away. If only looking at respondents under the age of 16 in Wave 1, there was no significant difference in follow-up rates. While those respondents missing in Wave 2 had, on average, a higher BMI and higher alcohol consumption, this difference became non-significant when correcting for the before-mentioned age difference. There was no significant difference in obesity rates or GPA. However, respondents lost to follow-up had on average a lower family income.

The loss-to-follow-up between Wave 1 and 4 was more skewed: Wave 4 non-responders were slightly older, more likely to be male, had a lower BMI, less obesity and a lower GPA.

Table 9.3. Characteristics of non-responders, as measured in Wave 1

	People not missing in wave 2	People missing in wave 2	People not missing in wave 4	People missing in wave 4
N	4834	1670	5114	1390
Age	15.6	17.2*	16.0	16.2*
Sex (male)	48%	50%	46%	57%*
BMI	22.4	23.0*^	22.6	22.2*
Obesity	10%	9%	11%	8%*
Alcohol units	7.9	11.7*^	8.8	9.4
GPA	2.8	2.8	2.8	2.7*
Ethnicity (white)	58%	55%*	60%	50%*
Income	48,199	46,054*	48,407	44,887

Note: * Significantly different from people not lost to follow-up at 0.05; *^ Significantly different but not if correcting for age difference

In addition to unit missingness, where respondents did not participate in a wave, in some cases not all questions were answered, resulting in item missingness. The rates of item missingness were relatively low, with the exception of smoking status, which was missing for 58.1% of respondents, and income, missing for 24.2%.

Table 9.4. Proportion of missing item responses

	Missing data in wave 1	Missing data in wave 2	Missing data in wave 4
BMI	3.3%	2.8%	1.6%
Alcohol units	1.5%	1.6%	1.4%
GPA	3.5%	9.4%	
Higher education			0.0%
Age	0.1%		
Sex	0.0%		
Ethnicity	0.1%		
Income	24.2%		
Smoking	58.1%		

Analysis showed that the missing income data is not random: students without income data are more likely to be non-white, older and have a lower GPA. However, missing income data is not associated with BMI. An explicit ‘income missing’ category was included in the analyses to partially account for the non-random missing data.

For smoking status however, the missingness pattern was strongly associated with both GPA and drinking frequency. This non-random pattern, combined with the high rate of missing data, meant that smoking was excluded as a confounder from the analyses for the US.

9.1.2. Obesity

Self-reported weight and height were used to calculate a BMI score for each observation in each wave. These were then used to create an obesity flag and an overweight flag using the child cut-off values defined by the WHO.

In Wave 1, 10% of students were obese and another 20% overweight. At the time of Wave 2, this had changed slightly to 11 % and 20% respectively. Prevalence at Wave 4 was much higher, at 33% and 31%.

9.1.3. Alcohol use

Three variables on alcohol use were selected from the survey: frequency of alcohol consumption, number of units consumed on average when consuming, and frequency of consuming 5 or more units in one sitting. The response options for the two frequency variables were reduced to include only three levels: rarely (including never), monthly (including “once a month or less”) and weekly (including daily).

In addition, a continuous variable was created for the number of units consumed per month, using the frequency of drinking and the average number of units consumed. This variable is an approximate value, as the categorical frequency of drinking was transformed into continuous values based on the mid-point of each category.

9.1.4. Educational performance

Both Wave 1 and Wave 2 asked respondents for their grades in maths, English, history (or social science) and science. However, not all respondents replied as some did not take the subject or did not receive a grade. The response options were A, B, C, or “D or lower”.

To create a single outcome variable, taking into account that some students received less than four grades, a GPA (grade point average) was calculated. Normally in the calculation of a GPA, a D would count for 1, and an F (the “or lower”) would count for 0. However, since this split was not available, all “D or lower” grades were counted as 1. This will have artificially inflated the GPA of some of the lower-scoring students, especially compared to other studies that have used 0.5 instead (Sabia, 2010[44]). However, since the analyses tested the overall trend of GPA rather than individual, categorical grades, the impact of this assumption on the results will be minimal.

9.1.5. Educational attainment

The variable “highest education level achieved to date”, which consisted of 13 different levels, was reduced to a binary variable to indicate whether the subject had completed any higher education. In this case completed was used rather than attended, to make the two groups more equal in size (39% has completed high education, while 76% has had ‘some’ higher education).

9.1.6. Confounders

Since students from different grades were included in each wave, age is an important variable to include in the analysis. In addition, a sex variable was extracted.

A large range of ethnicity categories were available, as well as a variable indicating whether the student was of a Latino or Hispanic background. To increase the numbers in each category, a single ethnicity variable was created that included the categories: Latino/Hispanic, other minority (including black, Asian-Pacific, Native Indian), other white (excluding Latino/Hispanic students who marked white). Income was used to correct for socio-economic differences and split into 5 quantiles to be used in the analysis.

Smoking was not included as a confounder, due to the high number of missing values for smoking status.

The United States cohort sampled its participants from schools. This clustered structure may influence the results, and was taken into account by using the robust *cluster* option in Stata.

9.1.7. Instrumental variables

For alcohol, the alcohol use of the respondent's three best friends was used as an instrumental variable (ranging from 0 to 3).

Religion was also explored as an instrumental variable. It was organised into three categories: religion prohibits the consumption of alcohol (including Baptists, Pentecostal, Methodists, Latter Day Saints (Mormon), Baha'i, Buddism and Islam); religious but religion does not specifically prohibit alcohol; and not religious. However, first-stage tests of the instrument found a low F-statistic, indicating that the instrument was weak. In other words, the religion variable was only weakly correlated with alcohol use. For this reason the variable did not work well as an instrument, and it was left out of the analyses.

No instrumental variables were available for obesity.

9.1.8. Final analysis sample

Table 9.5. Descriptive statistics of exposures and outcomes in the United States sample

	Male			Female		
Wave	***1***	***2***	***4***	***1***	***2***	***4***
Age	16.1	16.7	29.1	16.0	16.5	28.9
BMI	22.7	23.2	28.3	22.4	22.8	28.5
Obesity	11%	12%	31%	9%	10%	35%
Overweight	22%	22%	38%	18%	18%	26%
Units of alcohol last week	12.0	12.7	26.2	6.0	7.2	9.0
Alcohol consumption frequency						
Rarely	70%	67%		73%	72%	
Monthly	18%	19%		20%	20%	
Weekly	12%	13%		7%	8%	
Alcohol binging frequency						
Rarely	80%	77%		86%	85%	
Monthly	12%	13%		9%	10%	
Weekly	9%	10%		5%	5%	
GPA	2.7	2.7		2.9	2.9	
Any higher education			34%			44%

9.2. The 1970 British Cohort Study

The 1970 British Cohort Study follows the lives of more than 17,000 people born in England, Scotland and Wales in a single week of 1970. Subsequently, data was collected at 5 to 10 years intervals.

Table 9.6. Metadata per wave for 1970 British Cohort

Year	Age	N	Comments
1970	0	17,198	
1972	2	2,457	Substudy
1974	4	2,315	Substudy
1975	5	13,135	No weight/height
1980	**10**	**14,875**	
1986	**16**	**11,622**	
1996	26	9003	
1999/2000	**29/30**	**11,261**	
2004	34	9,665	
2008	38	8,874	
2012	42	9,841	
2016	46	TBD	

Note: waves in bold were used for this study
Source: http://www.cls.ioe.ac.uk

For the educational performance study, data from two waves was used: at age 10 and at age 16. There were 10,871 students who participated in both these waves. Other waves could not be used as 5 year-olds (yo) are not in school yet and in later waves, at 26yo, they had left school. While BMI data from earlier waves could have been useful, height and weight were not recorded in the 5yo survey.

For the educational attainment study, the wave at 16yo was compared to outcomes at 29yo. There were 8,328 students who participated in both these waves. The data from the 26yo wave was considered too early to determine final educational attainment.

Table 9.7. Overview of variables per wave

	10y	16y	29y
Obesity	Weight and height	Weight and height	Weight and height
Alcohol	N/A	Frequency alcohol Units alcohol last week Frequency more than 4 drinks in last 2 weeks	
Educational performance	Estimated reading age at 10 Academic performance	Estimated reading age at 16 Academic performance	N/A
Educational attainment	N/A	N/A	Age when left FT education Highest degree obtained
Confounders (fixed)	Sex Social class parent Ethnicity Income BMI for mother and father		

9.2.1. Missing data

In the public dataset of the cohort, the 10yo contains 14,870 respondents. At 16yo and 29yo, 27% and 30% of respondents from this initial population did not respond, respectively. In both waves, non-responders were more likely to be male and of a minority ethnicity, and had lower reading scores. Despite these similar patterns, only 48% of respondents missing from the survey at 16yo were the same respondents missing at 29yo.

Table 9.8. Characteristics of non-responders, as measured at 10 years old

	People not missing at 16yo	People missing at 16yo	People not missing at 29yo	People missing at 29yo
N	10,871	3,999	10,417	4,453
Sex (male)	50%	56%*	49%	59%*
BMI	16.85	16.9	16.88	16.85
Obesity	2.4%	2.8%	2.5%	2.5%
Reading age	10.10	9.60*	10.10	9.70*
Minority	10%	20%*	10%	18%*

Note: * Significantly different from people not missing, at a 0.05 significance level

In addition to non-response, there was considerable item missingness in the British Cohort Study. Especially at 16yo, when data collection was obstructed by a teacher strike, there were high missing rates for educational performance data. Analysis showed that these patterns were not random, with more data missing for men, people of minority backgrounds and with a low income. While there exist methods to deal with missing data, such as multiple imputation, these have been shown to be ineffective when the proportion of missing data is very large (roughly >60%) (Barzi and Woodward, 2004[74]). This means that the missing educational performance data at 16yo cannot be reliably used for analysis.

Instead, the United Kingdom data was used to look at educational attainment, where only a very small portion of the data is missing. A specific category was included for 'income missing' to account for the missing data in this variable. To understand the impact of the missing BMI and alcohol data at 16yo, multiple imputation models were run for selected analyses. These produced similar results to the original data.

Table 9.9. Proportion of missing item responses

	Missing data at 10yo	Missing data at 16yo	Missing data at 29yo
BMI	18%	0%	3%
Alcohol units	100%	31%	6%
Academic performance	18%	47%	
Reading age	34%	68%	
Income	16%		
Minority	0%		
Smoking		0%	
Higher education			0.4%
Left education age			0.5%

9.2.2. Obesity

BMI was deduced from weight and height information in each wave, using the WHO childhood obesity cut-offs for 10yo and 16yo to determine obesity and overweight status. However, only 2.5% and 2.7% of 10yo and 16yo respectively were obese, which will affect the statistical significance of some of the analyses. For this reason, obesity and overweight were also analysed in a combined metric for the United Kingdom data.

At 10yo and 16yo, weight and height were measured during a physical exam while at 29yo it was self-reported. Due to the high level of missingness at 16yo, self-reported values were used if no measured values were available.

9.2.3. Alcohol use

No alcohol use data was available for the 10yo, and the effect of alcohol use on educational performance could therefore not be measured. To understand the impact of alcohol use on educational attainment the number of alcohol units consumed last week, and the frequency of drinking was used. The latter was reduced to three categories: rarely, monthly and weekly drinking.

To measure the impact of binge drinking, the variable counting the number of times a respondent drank more than 4 units in the last two weeks was reduced to three categories: never, once or more than once.

9.2.4. Educational attainment

The wave at 29yo contains a variable describing the highest level of education achieved. This was transformed into a binary variable on whether or not the respondent had any higher education. In addition, the age at which the respondent left full-time education was used as a continuous variable.

9.2.5. Confounders

To correct for confounders, ethnicity, income and social class were used. The variable on ethnicity contained a large number of categories, and was reduced to a binary "minority" variable to indicate whether the respondent was of non-English origins. The social class variable was based on the profession of the father (and if there was no father, the mother). The six categories were combined into three: "partly or unskilled", "manual or non-manual", and "managerial or professional". The categorical income variable was reduced from 7 to 5 categories.

Smoking was not available at 10yo, but added as a confounder at 16yo for the educational attainment analyses. It was derived from the smoking habits question, indicating whether the respondent was currently a smoker.

9.2.6. Instrumental variables

The BMI of the mother and/or father was calculated to use as an instrumental variable for obesity. For alcohol use, five variables recording whether the respondent's older brother, sister, girlfriend or boyfriend, best friend and next best friend drank alcohol were used. Both the number and the percentage of people using were included as instrumental variables, as some respondents did not have siblings or a boyfriend or girlfriend. This would result in fewer people around them using alcohol around them, but is different from being around abstainers. Religion was included as three categories: religion prohibits the consumption of alcohol (including Islam, Buddhism and Sikh), religious but religion does not specifically prohibit alcohol, and not religious. However, first-stage tests of instrument strength showed that this variable did not improve the model and it was therefore not used as an instrument.

9.2.7. Final analysis sample

Table 9.10. Descriptive statistics of exposures and outcomes in the United Kingdom sample

	Male			Female		
	10	16	29	10	16	29
BMI	16.7	20.9	27.8	17.0	21.4	27.2
Obesity	3%	3%	27%	2%	2%	25%
Overweight	12%	11%	45%	15%	14%	38%
Units of alcohol last week		6.3	15.7		3.7	6.3
Alcohol consumption frequency						
Rarely		29%			38%	
Monthly		15%			13%	
Weekly		56%			49%	
Alcohol binging frequency						
Never in past 2 weeks		64%			70%	
Once in past 2 weeks		16%			14%	
More than once in past 2 weeks		20%			16%	
Age left FT education			17.6			17.8
Any higher education			27%			27%

9.3. The Russia Longitudinal Monitoring Survey

The Russia Longitudinal Monitoring Survey (RLMS) has collected data annually since 1992. The first two years the aim was to upgrade the systems in place for monitoring public health, and from 1994 onwards the RLMS provides a longitudinal dataset covering a nationally representative sample of households, and the individuals within it. It surveys adults as well as children, where the questionnaire for under-14-year olds is different from the adult questionnaire.

Educational performance, in the form of grades obtained, was only measured from 2010 onwards. In addition, while it was a standard question in the questionnaires on the children survey, it was only answered in about 30% of the surveys among children aged 14 and over. Therefore, the educational performance analysis was performed on the subset of children who were in school at any time between 2010 and 2015 and under the age of 14 (10,012 observations over 6 years, with between 1,482 and 1,803 students per year).

Educational attainment analysis was conducted based on alcohol use at 16 years old, and higher education attainment at 30 years old (the length of the study, 1994-2015, meant that the sample of people followed from 16 to 35 was too small). However, the alcohol use variable was missing for 39% of respondents (note: this is different from "no answer" or "does not want to say"). At 17 years old, this missing rate was 34%. As it appears that the question had been left out of the survey, rather than being unanswered, this study selected only people who had a recorded alcohol use at 16, or otherwise 17.

Their educational attainment was assessed at 30 years old, unless the subject did not participate at that age, in which case a potential reply at 29 was used instead. Results were adjusted for the age at which exposure and outcome were measured. For those people who had multiple questionnaire responses at the same age (i.e. they were 16 at the time that the 2002 and the 2003 survey were conducted, as the time between responses for individuals was not always exactly one year), the latest response was used. This resulted in a sample of 1,858 people with a recorded alcohol use at 16/17, of which 717 participated in the study again at age 29/30.

9.3.1. Missing data

For the educational performance 2010-2015 student subsample, alcohol data was not available. Therefore no analysis could be done linking alcohol use to educational performance. BMI on the other hand was widely available and only missing for 8.05% of observations. Household income, as derived from the household questionnaire, was missing for 5.4% of observations.

Loss-to-follow-up was relatively constant over the years, with between 65% and 76% of students included in the next wave, and a small percentage that returns to the study a wave later. The total population size remains stable as new students are added to the cohort as they start going to school. Non-responders did not differ from individuals did respond in terms of gender or income; but they were slightly older (9.3 year vs 11.3) and had a higher BMI (17.9 vs 19.0). However, when correcting for both age and BMI, the latter was no longer significant in predicting non-response.

Table 9.11. Loss to follow-up in the educational performance subsample

	Baseline wave:	2010	2011	2012	2013	2014
Next wave:	2011	74%				
	2012	2%	76%			
	2013		2%	75%		
	2014			2%	65%	
	2015			1%	4%	76%
	Permanently lost	23%	22%	22%	31%	24%

Table 9.12. Characteristics of non-responders in the educational performance subsample

	People not missing in next wave	People missing in next wave
Age	9.3	11.3*
Sex (male)	48%	50%
BMI	17.9	19.0*^
Obesity	14%	10%
Income	46226	47380

Note: * Significantly different from people not lost to follow-up at 0.05; *^ Significantly different but not if correcting for age difference

In the educational attainment sample, there was significant response difference between the ages 16/17 and 29/30. Only for 717 out of 1,858 (39%) individuals who participated at age 16/17 was there a response at age 29/30. However, non-responders were not significantly different in terms of age, sex, BMI, alcohol use, or household income. The only significant difference between the two groups was that people who dropped out were more likely to be Russian.

Table 9.13. Characteristics of non-responders in the educational attainment subsample

	People not missing at 29/30	People missing at 29/30
N	1,141	717
Age	16.3	16.3
Sex (male)	0.5	0.5
BMI	2054%	2070%
Obesity	2.3%	1.9%
Income (lowest bracket)	20%	19%
Alcohol (weekly)	7%	8%
Non-Russian	17%	9%*

Note: * Significantly different from people not lost to follow-up at 0.05

The educational attainment sample was selected based on the availability of alcohol use. In this sample, BMI was missing for 14.6% of people. Higher education, alcohol use and income were available for all participants who had a survey at age 29 or 30. Smoking status was missing for one respondent, and ethnicity for 3.77%.

9.3.2. Obesity

Obesity was calculated from parent-reported height and weight. For the educational performance subsample, which included only students below the age of 14 over the years

2011-2015, 22% was overweight and 13% obese. For the educational attainment sample, which was based on participants at 16 years old, 7% was overweight and 2% obese. This lower prevalence of obesity in older children in the RLMS has been noted by other researchers as well, who have postulated that the WHO cut-off limits for children may not be optimal for the Russian population (Wang, 2001[75]). As there are only 32 people obese in the educational attainment sample, of which 14 are lost to follow up, this category was combined with overweight for all analysis of educational attainment in Russia.

9.3.3. Alcohol use

The survey contained variables on any drinking in the last 30 days, and frequency of drinking in the last few days. These two variables were used to create an alcohol frequency variable which includes weekly (1 or more times a week), monthly (1 to 3 times in the last 30 days) or rarely (not in the last 30 days). The variables on alcohol use were missing for 39% and 34% of 16- and 17-year olds respectively. Therefore, a variable was created that recorded the drinking frequency at 17 if this information was not available at 16. In the regression analysis, a correction as made for the age at which alcohol use was recorded.

While the questionnaire includes a large number of questions on the consumption on different alcohol beverages, this data was not consistent and for a large part missing. As such, no linear variable on the amount of units drunk could be included.

9.3.4. Educational performance

Educational performance was based on the ‘progress estimation’ variable, which asks what grades the student obtained on average (i.e. “Almost all the grades are fives”, “Basically all the grades are fives and fours”), using the Russian scale of 1 to 5 with 5 being the highest. The categorical variable was translated into a linear one as follows:

Table 9.14. Grade variables in the RLMS cohort

Original categorical value	New linear value
Almost all the grades are fives	5
Basically all the grades are fives and fours	4.5
Basically all the grades are fours	4
Basically all the grades are fours and threes	3.5
Basically all the grades are threes	3
Basically all the grades are threes and often twos	2.5

9.3.5. Educational attainment

Educational attainment was measured at age 30 (or 29 if no data was available for 30), from the variable recording the highest diploma achieved. This was converted into a binary variable, indicating whether the individual had completed any higher education (33% of 29/30-year olds).

9.3.6. Confounders

Age and sex were included as confounders for all analysis.

In the educational attainment sample, smoking was available and included as a binary variable for current smoker. Nationality was explored as a proxy for ethnicity; however 87% of responses were Russian. Therefore a binary variable was created for “non-Russian”.

Economic rank was available in the questionnaire, and was transformed from a 9 step to a 3-step ordinal variable, to increase the size of each group.

For the educational performance sample, which was based on only Child questionnaires, no information was available on smoking status, nationality or socio-economic class.

From the household questionnaire, household 30-day income was extracted, and matched to the individuals based on the round-specific household ID. This continuous variable was converted into a five-step ordinal variable. While for adults an individual income was available as well, the household income was used instead to account for non-working spouses and young adults in education.

9.3.7. Instrumental variables

Religion was explored as an IV, but this variable was missing for 68% of observations. No other instrumental variables were available in the Russian dataset.

9.3.8. Final analysis sample

For Russia, the educational performance sample was based on the waves 2011-2015, including only students under the age of 14.

Table 9.15. Descriptive statistics of exposures and outcomes in the Russian Educational Performance sample

	Male	Female
Age	9.8	9.8
BMI	18.3	18.1
Obesity	16%	10%
Overweight	23%	21%
Average grade	4.0	4.3

For the Russian education attainment sample, respondents were selected based on their age.

Table 9.16. Descriptive statistics of exposures and outcomes in the Russian Educational Attainment sample

	Male	Female
Age 16/17		
BMI	20.8	20.5
Obesity	2%	2%
Overweight	9%	6%
Alcohol consumption frequency		
Rarely	71%	70%
Monthly	20%	24%
Weekly	9%	6%
Age 29/30		
Any higher education	29%	37%

9.4. The Christchurch Health and Development Study

The Christchurch Health and Development Study (CHDS) follows a cohort of 1,265 children born in the New Zealand city of Christchurch in 1977. A total of 953 people participated at age 16 (which was used as the exposure year), and were included in the sample for this study. At 18, a standardised reading score was calculated, which was used to measure educational performance. At 25 years, the age at which the participant left full-time education was calculated. At 35 years, the highest educational qualification obtained was recorded.

9.4.1. Missing data

A total of 312 participants of the cohort of 1,265 did not have data for the exposure year, at 16 years old. There participants are similar in ethnicity and educational outcomes as the participants who did participate at 16, but they have a significantly lower income and social class.

Table 9.17. Characteristics of non-responders at age 16

	Participated at 16	Did not participate at 16
n	953	312
Maori/Pacific Islander	14%	16%
Social class (lowest class)	25%	34%*
Income (lowest group)	9%	15%*
Burt reading score	97.3	98.4
Age leaving FT education	18.8	18.8
Any higher education	43%	39%

Note: * Significantly different from people not lost to follow-up at 0.05

Within the study sample of 953 people with data for age 16, missing data (due to non-completion as well as loss to follow-up) was limited (see Table 9.18).

Table 9.18. Missing data for CHDS study sample (n=953)

	Missing
Maori/Pacific Islander	0.0%
Social class	0.0%
Income	0.1%
Alcohol consumption frequency	0.0%
Binge drinking	4.7%
Burt reading score	2.8%
Age leaving FT education	2.6%
Any higher education	3.3%
Smoking status	0.0%

9.4.2. Obesity

The CHDS did not contain information on weight or obesity status.

9.4.3. Alcohol use

Alcohol use was measured at 16 years old. The frequency used in the dataset was converted into three categories, of rarely, monthly and weekly drinking. While a variable was available on the number of drinks consumed each time, this could not reliably be combined with the frequency variable to obtain a linear variable of unit consumption.

A variable was available which measured the maximum number of drinks consumed on a single drinking occasion in the past 3 months. While this could be used to create a binary binge drinking variable, the long time frame meant that around 40% of the respondents were in the binge drinking category, and this did not truly represent high risk drinking.

Instead, two variables were used to create a binge drinking measure: usual number of drinks in one sitting, and frequency of drinking. Individuals who reported usually drinking 5 or more drinks in one sitting were included in the binge drinking category, and the frequency of their drinking was used to create groups who "usually binge drank, monthly" and "usually binge drank, weekly".

9.4.4. Educational performance

Educational performance was measured at age 18, using the BURT word reading test (Gilmore, Croft and Reid, 1981[76]). This test score reflects the number of words correctly read from a list of 110 words. This test was only available at 18, so no fixed effects analysis was possible.

An issue with the BURT reading score is that it was designed for younger children. At the age of 18, the average was score was 97.4 with a standard deviation of 13.0. As a result, in our sample 80% of participants had a score between 91 and 110.

9.4.5. Educational attainment

The highest educational qualification attained was measured at age 35. The existing categorical variable was recoded into a binary variable flagging whether the participant had completed any higher education. A difference was made between lower level tertiary qualifications (level 4 and below) and higher level tertiary qualifications (level 5 and above), as this is the definition employed in the New Zealand census to measure the rate of higher education attainment.

The age at which the participant left full time education was measured up until the age of 25. Participants still in education at that age, or who were lost to follow up, were considered censored.

9.4.6. Confounders

Age, sex, ethnicity (binary for Maori/ Pacific Island or other) and smoking status (binary for smoking at least weekly or not) were included as confounders for all analysis.

Income was available in the original dataset as the average decile rank over ten years, covering the period between birth and age 10. This linear variable was transformed into a categorical variable by assigning the average ranks (ranging from 1 to 10), to five (i.e. 1-2 = rank 1, >2-4 = rank 2 etc).

Two variables on socio-economic status (SES) were available, one measured at birth and the other at age 14. Since the one at age 14 was missing for 21% of participants, the SES score at birth was used. This is the Elley & Irving New Zealand Socio-economic Index classification of paternal occupational status (Elley and Irving, 1976[77]). The six categories in this variable were reduced to three: "semi- or unskilled", "skilled or clerical", and "managerial or professional".

9.4.7. Instrumental variables

The alcohol use of friends was used as an instrumental variable for the alcohol frequency variable. This variable was coded in three categories: none, some and most. The variable was included at 16 years old, and for the previous year at 15 years old.

9.4.8. Final analysis sample

Table 9.19. Descriptive statistics of exposures and outcomes in the New Zealand sample

	Male	Female
Age 16		
Alcohol consumption frequency		
Rarely	49%	50%
Monthly	33%	40%
Weekly	19%	10%
Usual binge drinking		
Rarely	74%	81%
Monthly	14%	13%
Weekly	12%	6%
Age 18		
Burt reading score	96.3	98.3
Age 25		
Age leaving FT education	18.5	19.0
Age 35		
Any higher education	36%	50%

9.5. The German Health Interview and Examination Survey for Children and Adolescents

The first wave of the KiGGS study was conducted between 2003 and 2006. This baseline study collected comprehensive health data on a nationally-representative sample of children and adolescents. Afterwards, KiGGS was continued at the Robert Koch Institute in the form of a long-term study, and forms part of countrywide health monitoring. Data on the first follow-up wave (KiGGS1) was collected between June 2009 and June 2012. KiGGS2 took place between 2014 and 2017, but the data was not yet available at the time of this study. The baseline study included 17,640 children between the ages of 0 and 17, from 167 cities and municipalities in Germany.

9.5.1. Missing data

Of the 17,640 children included in the baseline study, 11,992 were included again in the follow-up (68%). The participants lost to follow-up were significantly different from the follow-up sample on many characteristics (see Table 9.20). To solve this issue, the KiGGS study has created weightings to account for this. These weightings were used in all analyses.

Table 9.20. Characteristics of participants lost to follow-up

	Participated in follow-up	Did not participate in follow-up
n	11992	5648
Exact age	8.2	9.2*
Sex (% male)	49%	54%*
Migrant	10%	25%*
BMI	17.9	19.0*
Alcohol units	3.0	3.7*
Average grade	2.6	2.9*
SES (lowest quintile)	10%	28%*

Note: * Significantly different from people not lost to follow-up at 0.05

Missing data within the complete sample was limited for most variables. Because grades were only available for students in school, the sample size for the analysis was reduced. For the lagged regression, only students who were in school in the follow-up wave could be used (from around 8 years old to 17 years old, n= 6,777). For the fixed effects analysis grade information was required for both waves, reducing the sample to 2,302. Grades were missing for 13% of eligible students in the baseline sample, and 9% in the follow-up.

Table 9.21. Missing data for KiGGS study sample (n=11,992)

Variable	Percent missing
Sex	0%
Age	0%
BMI wave 1	1%
BMI wave 2	5%
Alcohol units (if aged >10)	0%
Grade wave 1 (if aged 8 to 16)	13%
Grade wave 2 (if aged 8 to 16)	8%
Migrant	0%
SES	1%

9.5.2. Obesity

BMI was deduced from the values measured during the anthropometrical exam in the baseline study.

9.5.3. Alcohol use

Variables on the consumption of beer, wine and schnapps were available in the baseline study for participants over the age of 11. However, by the time of the follow-up survey, even the youngest participants with alcohol data were almost all 17 and the large majority of the sample therefore did not have grade data any more. For this reason, no analysis on alcohol use could be done.

9.5.4. Educational performance

Grades for German and mathematics were available in the baseline and the follow-up wave. These were measured on a scale from 1 to 6, with 1 being the highest score. The average of the two subjects was used as the linear outcome for educational performance.

9.5.5. Educational attainment

The follow-up period in the KiGGS data was not long enough to determine educational attainment.

9.5.6. Confounders

Sex and age were included as confounders in all analyses. Socio-economic status based on income was available in the dataset and the quintiles were used as a categorical variable. Migrant status was included as a yes/no variable.

Smoking status was available, but only for students aged 11 or older. Similar to the issue with alcohol use, only few participants with a recorded smoking status were still in school and obtaining grades by wave two (in addition, these were only students who were 11 at the time of the baseline study, and smoking prevalence was near zero). For this reason, smoking was not included as a confounder.

9.5.7. Instrumental variables

The BMI of the mother and father were used as instrumental variables for obesity. No instrumental variables were available for alcohol.

9.5.8. Final analysis sample

Table 9.22. Descriptive statistics of exposures and outcomes in the German sample

	Baseline		Follow-up	
	Male	Female	Male	Female
Age	8.5	8.5	14.1	14.4
BMI	18.3	18.3	20.3	19.7
Obesity	9%	7%	7%	4%
Overweight	17%	17%	20%	13%
Average grade	2.8	2.6	2.7	2.5

9.6. The Prevention and Incidence of Asthma and Mite Allergy study

The primary aim of the PIAMA study was to research the impact of risk factors on the development of asthma and mite allergy during the first 8 years of childhood. After this time point, follow-up was continued until 17 years old, to study longer term effects as well as other chronic diseases.

Around 4,000 participants were recruited before their birth in 1996 and 1997. Questionnaires were completed annually until the age of 8, and then at 11, 14 and 17 years old approximately. The last 3 waves were considered for this study.

Academic performance was measured between 11 and 17 years old, and the exposures were therefore taken at 11 years old. It was impossible to determine whether the exposures recorded at 14 years old preceded the educational outcomes, and they could therefore not be used to study a temporal, causal relation.

9.6.1. Missing data

The sample at 11 years old (n=2,641) was used as the basis for this analysis. At 17 years old, 2,096 questionnaires were completed and 1892 participants (72% of 2641) completed questionnaires at both ages (see Table 9.23). The students lost to follow-up were more likely to be male, and have parents with a lower education. There was however no difference in baseline BMI of the participants.

Table 9.23. Characteristics of non-responders at age 17

	Participated at 17	Did not participate at 17
n	1892	749
Exact age	11.0	11.0
Sex (% male)	48%	55%*
Minority	7%	8%
BMI	17.5	17.7
BMI mother	24.5	24.9
BMI father	25.7	26.5*
Education mother (% low)	17%	28%*
Education father (% low)	20%	29%*

Note: * Significantly different from people not lost to follow-up at 0.05

In the sample that was complete, there were some missing values for BMI (both of the participant and of the mother and father), and for teacher's assessment at age 11 (see Table 9.24). The analyses looking at school level include therefore more participants than those comparing the school level to the teacher's assessment.

Table 9.24. Missing data for PIAMA study sample (n=1,892)

	Percentage missing
BMI at 11	11%
BMI mother	10%
BMI father	13%
Education mother	0%
Education father	1%
Minority	2%
School level at 17	5%
Teacher's assessment at 11	17%

9.6.2. Obesity

Obesity status was deduced from a calculated BMI at ages 11 and 17. At both ages, the prevalence of obesity was low (2.6% and 2.1% respectively). Therefore, obesity and overweight were combined in the analyses.

9.6.3. Alcohol use

While available in the dataset, alcohol use at 11 was minimal, and was therefore not considered as an exposure in this study. However, it was included as a confounder in the obesity models.

9.6.4. Educational performance

Educational performance was measured using the different high school levels that exist in the Netherlands. At 17 years old, the level of high school was determined and divided into two categories: VMBO/MBO (vocational training) or HAVO/VWO/HBO/university (higher secondary or tertiary education).

In addition to this variable, the educational performance was compared to the teacher's assessment given at age 11/12. At age 11/12, when children leave primary school to go to high school, their teacher provides an assessment as to the appropriate level of school. However, students can move between the different levels depending on their performance in school. Therefore, the assessment at age 11/12 was compared to the actual level of school students were in at age 17. A binary variable was created that indicated that the student ended up in a lower level than assessed. Note that for students who had moved on to tertiary education at age 17, their level of tertiary education was used to identify the corresponding level of high school. This may underestimate educational performance in some cases, as students can choose to follow a lower tertiary education than their high school level allows.

9.6.5. Educational attainment

The cohort has not yet reached an age at which final educational attainment can be measured.

9.6.6. Confounders

Exact age at the time of the questionnaire and sex were included as confounders for all analysis. Smoking status was available, but only 2 students were regular smokers at age 11, and this variable was therefore not included.

Ethnicity was available in three categories: Dutch, Western or Non-western. However, due to the small number of participants in the latter two categories (ca. 5% and 4% respectively), they were combined into a binary 'minority' flag.

No income or social-economic index variables were available. Therefore, the educational attainment of the mother and of the father was used to correct for socio-economic status. This was divided into low, intermediate and high, reflecting primary school or lower secondary education; higher secondary education or intermediate vocational traning; or higher vocational education or university.

9.6.7. Instrumental variables

For obesity status, the BMI of the mother and of the father were used as instrumental variables.

For alcohol use, no instrumental variables were available.

9.6.8. Final analysis sample

Table 9.25. Descriptive statistics of exposures and outcomes in the Dutch sample

	Male	Female
Age 11		
BMI	17.5	17.6
Obese	4%	1%
Overweight	15%	13%
Age 17		
% at higher level of high school	65%	68%
% at level below assessment	19%	9%

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